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OPTIMIZATION OF LONG-TERM CONSUMER MAGAZINE ADVERTISING MEDIA SCHEDULES

By

JUNGSIK CHO

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Jungsik Cho

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The goals of this study are 1) to develop a media selection framework that possesses the primary elements of the media selection process and that shows a global picture of how media selection works, and 2) to verify the role of each element in the model.

Based on a content analysis of seven major media planning texts, the author has determined the elements that are important in the media selection process and has proposed a normative media selection model. Yet, the role of each element in the media selection process is still unknown. Due to both the complexities involved in this subject and the lack of past research, the validation of the model is limited to the scope of consumer magazines and to the elements that are directly involved in the media impact estimation process. The elements tested include the timing of advertising, media quantity discounts, message effects, and carryover effects.

To verify the model, a computer program that reflects the normative model was developed. This program will select the schedule generating the most media impact, based on gross rating points. Through the review of the empirical findings related to each element, this study has determined the operational definition of each element and the empirical relationship among elements in the model.

By analyzing a total of 720 optimum schedules produced from the model with different treatments, this study has determined whether the use of any element in the model makes the vehicle selection of the optimum schedule different and whether such different vehicle selection influences the media impact. Any elements that affect the vehicle selection and the media impact have been considered to be effective in the media selection process.

The study found a decisive effect of the timing of advertising on the media selection process. When the model evaluated all the possible types of advertising schedules, it was able to recommend a more effective optimum schedule than the model which evaluated continuous schedules. In addition, the present study has found partial support for an impact of the media quantity discounts and an impact of the message effects.

CHAPTER 1
INTRODUCTION

Media Selection Models

When the role of advertising is to tell prospective customers about products, the role of media in advertising is to deliver these messages to those prospects. To convey messages efficiently, the media practitioner is faced with the critical decision of timing, and media and vehicle selection in media. This seemingly simple problem has certainly given media practitioners a truly challenging task and has made them struggle to find the better media schedule that can carry their messages to customers efficiently and effectively. Developing a typical media schedule may be easy, but guaranteeing the best media schedule for a brand is not. This problem can be specified in the following fashion: *From a set of media and vehicle alternatives, which options should be selected and when should they be used in order to maximize the value of the intended objective, given an advertising budget and various information about the marketing and advertising situations.* Media selection models play their part in the solution to this problem.

Complexity of the Problem

The decision of timing, and media and vehicle selection in media is indeed a complex problem because of the number of media decisions that must be made, because

of the surplus of seemingly reasonable choices usually available, and because of other advertising or marketing variables related to the media decisions such as the quality and number of messages, the product and consumer characteristics, or the users' previous experience. Townsend (1988) supports this argument by reporting "the number of advertising media choices is increasing with 11,500 magazines in print, and 22 network and cable television stations available to the average consumer" (p. 8).

As a result, the media planner who is supposed to develop the best possible plan for a brand must choose one plan from the several millions or billions of possible schedules. As a simple case, in order to select the best monthly schedule from a group of 10 vehicles with a maximum of two insertions each, an advertiser should consider an evaluation of 59,049 possible schedules ($=3^{10}$). Even with this rather small number of alternatives, it would be almost impossible to evaluate every schedule without the use of a computer. This is a mere single media evaluation problem with a very small number of possibilities, and the number of options would easily explode if restrictions were relaxed. If a planner decided to use two media categories with the same types of options (i.e., 10 vehicles with two insertions each), a total number of possible schedules to be evaluated to obtain an optimum schedule quickly increases to 348,674,401 ($=3^{10} * 3^{10}$) (Lancaster, 1987, pp. 1-2).

Timing of advertising is another concern in the selection of media. If a planner decides to develop a plan which goes beyond a monthly time frame, he/she will face an ever-challenging three-dimensional decision: timing, vehicle selection, and media. The Media Group (1989) synthesizes this problem in the following way: *If a monthly schedule is optimum, should it be used month after month, or should vehicles be alternated to increase impact?* If a planner believes the repeated use of a monthly plan is not plausible, the size of the problem he/she faces becomes even greater. For example,

an option of 10 vehicles with two insertions each for a 12 month period would require an estimation of $59{,}049^{12}$ ($=(3^{10})^{12}$) possible schedules!

Besides the multiplicity of alternatives, the use of valid mechanisms in evaluating each schedule adds more complexity. If a planner decided to evaluate the schedule based on the linear product of vehicle variables, the computer program which is designed to select the best schedule based on that linear objective function can do this task without taking more than a few minutes even with a typical 16 MHZ[1] IBM PC machine. *Objective function* refers to a function which assigns a value to a given media insertion schedule in order to define the best schedule among the alternatives. However, if a model examines both *exposure distribution* of each media schedule to calculate more sophisticated objective functions and considers target audience, message criteria, or cost efficiency of the schedule as it should, a calculation of a single schedule may take an extended amount of time. *Exposure distribution* refers to the percentage of the target exposed to each level of frequency. Knowledge of the exposure distribution for a particular media schedule is important in the evaluation of media schedules in four ways: 1) "it shows the proportion of the target audience receiving few or many exposures to schedule vehicles, which provide more complete information than does average frequency figure" (Leckenby and Boyd, 1984a, p. 1); 2) "it illustrates the skewness of the distribution" (Leckenby and Boyd, 1984a, p. 1); 3) it is necessary to determine *reach*, the proportion of the target audience exposed one or more times to the vehicles or messages in a schedule; *effective reach*, the proportion of the target audience exposed three or more times to the vehicles or messages in a schedule; *frequency*, the number of times target members are exposed to vehicles or message in a schedule; and

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[1] Clock speeds are designated by the number of pulses or cycles per second. 16 MHZ refers to a computer's capability of running 16,000 cycles or pulses per second.

gross rating points (GRPs), the mean of the exposure distribution (Danaher, 1989), and 4) it can be used in media selection when an advertiser may want to maximize some function of the *exposure distribution* such as reach, GRPs, or effective reach.

An increasing burden of complexities could be added without end. To cope with advertising media selection, a planner may have to consider other media variables such as target audience, media quantity discounts, or media and vehicle characteristics and marketing and advertising variables such as message quality, competitive spending, product seasonality, or geographic disparity in sales.

A More Comprehensive Model

To efficiently manage this complex problem, media researchers have developed computer models which are designed to produce the best advertising media schedules. A model which has an ability 1) to scan many schedules, 2) to estimate audience exposure, and 3) to be comprehensive is considered to be ideal (Rust, 1985), but few models have fully met these criteria. A model which evaluates all possible options, has an ability to examine all the criteria related to the advertising media planning process (e.g., timing, carryover, exposure distributions, etc.), and still can produce an optimal schedule within a reasonable amount of time can be considered an ideal model. Such a model may never be possible to develop because of the time consuming computation procedure. Simple models which only examine a few criteria can be practical enough to generate an optimal solution within a short time, but that solution may not be valuable to those who have to consider many important aspects of marketing, advertising, and media factors to develop the best media schedule. This is because the model cannot incorporate other unexamined but important media factors.

To make the model comprehensive but practical, two approaches have to be considered for this problem. First, the model examines only necessary and sufficient media planning variables to produce the optimum plan and sacrifices unimportant factors from its evaluation. The model also can ignore some factors which do not affect the selection of the media, vehicle, and insertions if they are proven not to do so. Any practical model cannot examine all the possible criteria due to the number of options to be evaluated. At the same time, this model should not ignore factors which can influence the outcome of the solution, because these factors can jeopardize the validity of the solution. The most practical and comprehensive model could be the one which explores all the necessary and sufficient media planning criteria to produce an optimal solution. The second approach is to sacrifice the optimality of the solution. Without evaluating all the possible options, the model tries to find the better solution, if not the best, using searching heuristics. So far, several heuristic media selection models such as MEDIAC (Little & Lodish, 1969), ADMOD (Aaker, 1975), or VIDEAC (Rust, 1985) have been developed, but the ability of finding an optimum solution with these heuristics has never been proved. The validity of heuristics will be discussed in more detail in the next chapter. This approach can be dangerous unless the heuristics are tested for the ability to find a solution close to the optimum one, since no one will be sure how effective the solution from the heuristics might be. This second approach could only be recommended if it takes an excessive and impractical amount of computer work for a model to obtain the optimum schedule even using the first approach.

Purpose of the Study

This study investigates the first problem, the exploration of factors involved in the media selection process and the development of a more comprehensive but parsimonious model for media selection. To do so requires the development of a normative media selection model that embraces all the conceptually important variables in the media selection process, whether these elements make an impact on the selection of the vehicles or not. The verification of this model shows the relationship of each element to vehicle selection, and reveals a more integrated picture of the media selection process. The author believes this normative model will guide the complex media selection problem in a proper direction, and will make each problem more manageable and systematic. Therefore, a comprehensive and integrated media selection model is proposed and every element in the model is tested to observe the impact of each element on media selection and to achieve the parsimony of the model. Thus, the purpose of this study is 1) to provide a complete and accurate picture of the ideal media selection model, 2) to propose a model which closely resembles this ideal model, and 3) to test how each factor in the proposed model affects the selection of timing and space in media.

Rationale

There are basically two scientific approaches a researcher can take to explain a phenomenon: induction and deduction. Induction uses "particular or specific instances as observed by the scientist to arrive at general conclusions or axioms" (Severin & Tankard, 1979, p. 14). The inductive approach first focuses on some specific aspects of the entire problem. Then, by accumulating these specific answers, the inductive

approach tries to find a general understanding of the problem. However, this approach always poses a danger of misspecification of the problem. At any moment, researchers lack a complete knowledge of the phenomenon in question, and any new findings may lead to a different general understanding.

On the other hand, deduction begins "with what is general and applies it to particular cases" (Severin & Tankard, 1979, p. 14). Once researchers have the correct general framework of the phenomenon, there is less danger of getting lost. However, the development of a general model is a difficult task.

The author has presented the two methods of scientific inquiry because the purpose of the present study is more understandable with the knowledge of scientific inquiry. Certainly, this dissertation opted for the deductive approach. To better explain the media selection process, the author first suggests a general media selection model (i.e. general model) and then shows how each concept in the model is related (i.e. specific aspects of the problem). There are two reasons why deduction is the right approach for the media selection problem. First, the media selection process is a complicated process, so that it is hard to figure out a global picture of this whole subject by collecting some specific answers within this subject. Second, there is an objective way of developing a general media selection model. The media selection process, in fact, focuses on the same phenomena on which media planning focuses. The media selection process, the decision of timing and spacing of advertising, requires the consideration of all the important elements involved in media planning. Then, the development of a normative media selection model is possible by a content analysis of the media planning texts and by sorting out the important elements in the media planning process. The model can be based not on the author's intuition, but on the organization of thoughts of many leading media planning researchers. In sum, the

media selection process is so complicated that the inductive approach is hard to handle, and the development of a normative model is possible using the deductive approach.

Without understanding the nature of the media selection process, model builders have no way of developing a good media selection model. If model builders do not have a normative media selection model framework, they will not know how effective the present media selection model is and where the future media selection model building should go. At most, they can develop a model that is more practical and user friendly, but they will not be able to know which elements are missing in the model. This problem becomes more obvious if anyone compares the elements that past media selection models have incorporated, which will be discussed in more detail in the next chapter. In fact, any two models examine the same types of media variables in estimating media impact, unless the two models are developed by the same person. Therefore, only after the researchers have a general framework of a good media selection model and after they understand the nature of the media selection process better, will the media selection problem become more manageable.

While obtaining an optimal schedule is a complex task, the benefits are certainly appealing. It has been an irony that media planning, the most quantitative and scientific discipline in advertising, could neither address the most fundamental problem, a decision of timing and spacing in media, nor free itself from subjectivity to answer this question. In a field which has advanced enough to calculate the efficiency of a media vehicle and to estimate the likely impact of a certain schedule, no one is really sure if a media planner's so-called recommended schedule could produce the best impact of all. By evaluating all the possible options with an ability to be comprehensive, a model builder can guarantee the optimality of the solution.

A long-term optimum schedule also can be a solution for media budget allocation and timing of an advertising problem. This has been another challenging subject in media research, since optimal output supplies information of specific timing of advertising as well as the number of insertions in each vehicle. In the study of budget allocation and timing of advertising, researchers have focused on a way of allocating advertising budgets across time and knowing when and how much to advertise to maximize the impact (e.g., Simon, 1982; Katz, 1980; Zielske and Henry, 1980; and Strong, 1977). It will be possible to answer this question simply by calculating media costs for each month in a given solution.

Organization of the Dissertation

Chapter 2 presents, in more detail, criteria which are important in the media selection process by reviewing both the major media planning publications and the works of previous media models to discover how close these past models have been to the ideal media selection framework. This review will give a better view of what has been lacking and what is needed in the study of media selection models and will provide a sense of how this research is positioned among the works of others.

Chapter 3 presents in greater detail the reasons behind this research undertaking, showing why such a model is necessary to improve the quality of optimal solutions. The decision to choose consumer magazines to test the model is explored next, along with a brief description of the characteristics of the medium.

These background works set the stage for Chapter 4, which offers the more comprehensive media selection models in detail, explaining all of the major elements

involved -- the objective function to be used, the optimizing constraints, and the media strategy variables.

In the method chapter (Chapter 5), each element of the model is investigated for its impact on the optimal solution. To do so, the author first proposes several hypotheses to test each element of the model. Later, the description of the data base to be used, analytical procedures, and methodological limitations follow.

In Chapter 6, Chapter 7, and Chapter 8, the findings of the verification analyses and the results of hypotheses testing are presented. Finally, summaries, conclusions, implications, and suggestions are provided in Chapter 9.

CHAPTER 2
REVIEW OF LITERATURE

Overview

This chapter, which starts with the exploration of factors important to the development of the media selection models, is basically a review of the *media planning process* since the goal of media buying is to achieve media strategies and objectives effectively. As Brennan noted in 1951, "Space or time buying, then, is a matter of selecting media most suited to the objectives that an advertiser seeks to obtain." This is followed by the review of the major advertising media selection models over the years. The performance of the models found in the past is evaluated according to the major elements of the advertising media planning process which will be proposed in the next section. These elements include the objective function, optimizing constraints, the number of media evaluated, searching routine, and the examination of media strategy variables. Where appropriate, this chapter reviews empirical evidence that is concerned with the above-mentioned elements and that is found in other related advertising studies.

The Elements of the Ideal Media Selection Model

The Media Planning Process

The media planning process, at a glance, can be seen as the buying of media space and time in an advertising schedule to deliver an advertising message. To do it efficiently and effectively, however, requires a more thorough consideration of the

marketing and advertising situation. As Lancaster and Katz (1988, p. 4-1) assert, "Whenever a media planner is faced with a new advertising or media planning problem or assignment, it is vital to conduct a thorough situation analysis before recommending a course of action . . . . A situation analysis can focus on any one of the elements of the marketing and advertising mix."

The consideration of a marketing situation would involve an examination of the history of the company and brand, current sales and sales trends, market share, the elements of the marketing mix (for example, market segment, characteristics of products, and distribution channel characteristics), or economic, regulatory, and social factors and trends. An analysis of the advertising situation analysis would require a consideration of advertising appropriation and budget, competitive spending in advertising, target audience, and the evaluation of the advertising message for the brand (Katz, 1988).

After the marketing and advertising situation analysis has been completed, the next step followed by a media planner is to develop measurable media objectives which will recognize marketing and advertising goals. In addition to setting marketing and advertising objectives, the information obtained from marketing and advertising situation analysis can be helpful in developing media objectives and even in the actual selection of media. These media objectives, of course, must fit in with and support the marketing and advertising objectives that have already been determined. Media objectives serve the purpose of helping media planners decide to which media they want to advertise, and it is important to state media objectives as quantitatively as possible (Scissors and Bumba, 1989). The relationships among these three objectives are well described by Lancaster and Katz (1988) and are presented as follows:

> While marketing objectives deal with sales and the market share of the product, the advertising objectives are concerned with the communication effects that are required to help achieve marketing goals. Finally, media objectives consider the effective reach of the media plan that is needed to achieve advertising goals. (p. 5-1)

Once a media planner has developed media objectives, he or she begins to outline the specific principles of the media function which are designed to implement the overall media objectives. These specific principles are called *media strategies* and should be designed to accomplish effectively the stated goals. The examples of these strategic variables could include target audience, geographical distribution, cost efficiency, and timing of advertising. In media planning, there are many opportunities to use strategy, but inevitably a problem arises in trying to find a way to know, objectively, which course of action will be optimal. Scissors and Bumba (1989) support this argument by writing the following:

> The mental process of weighting media strategy alternatives presents a formidable task because there are many alternatives to think about at any one time. While thinking about audience sizes, a planner must, at the very same time, be thinking about the cost efficiencies, availabilities of media units, discounts that could change the whole plan, the effect of competitors, the creative strategy and execution, the amount of money that is available, and the time available to accomplish objectives and that is only a partial list. (p. 221)

The actual buying of media space and time in an advertising schedule is the last step that a media planner takes. Only after all the marketing and advertising situational analyses have been completed, after advertising and marketing objectives have been examined, and after media objectives and strategies have been determined, can the media planner decide which media and vehicles to use, the number of insertions in each vehicle to select, and when to advertise. Of course, these tactical decisions should compliment all the marketing, advertising, and media goals as well as media strategies.

In other words, the advertising schedule developed by a planner should be the one which will be most likely to accomplish specific media objectives which will eventually result in advertising and marketing objectives. To summarize, typical media planning begins with the examination of the marketing and advertising situation. Based on the understanding of marketing and advertising environment of a brand, a media planner develops measurable media objectives. Then, he or she outlines media strategies which are designed to implement media objectives. Finally, the actual media buying decision can be made based on the above instructions.

The Media Planning Process and The Media Selection Model

The scope which the media selection model covers is basically the same as the one covered by media planning. Both concern the problem of media buying, require an examination of the marketing and advertising situation, and involve the decision of media objectives and strategies. However, the media selection model and the media planning process are not identical in that their focuses on the subject are different. As illustrated in the above section, the media planning process focuses on the objective decision making of each element. Here, more emphasis is placed on how to objectively develop media objectives, strategies, and tactics. Therefore, the first step is to analyze the marketing and advertising situation. Objective and strategy setting and tactical decision making follow.

Another primary goal of the media selection model is to suggest the media schedule which will deliver an advertising message to an extent that the stated media objectives can be achieved. In other words, the model should enable the planner to decide the buying of media space and time in an advertising schedule so as to achieve

the media objectives. To do so, the media selection model typically evaluates a schedule based on some function of the media objectives, and this function is, of course, supported by other strategic and situational variables. A more detailed explanation of the structure of the media selection model will be presented in the next section. In sum, both the media selection model and media planning are concerned with the same subject, while their focuses on the subject are somewhat different. Figure 1 is a brief look at the media selection model.

Figure 1. A Brief Look at the Media Selection Model

Lack of a Media Planning Framework and Concepts of the Ideal Media Selection Model

Although a great number of media selection models have been proposed since the 1960s, much is unknown and unclear concerning what a good media selection model should be. Most model builders have put much effort into the technical aspects of the model, such as reducing the time required for analysis or improving an optimization algorithm, rather than on more fundamental issues, such as what elements should be examined in the model. As Katz (1988, p.8) notes, "Within media research itself, while much effort is spent on highly focused efforts such as improving media models to evaluate media schedules, there has been little, if any, attempt to integrate all of the various aspects of the media planning process into a cohesive and comprehensive framework that would show, at a glance, all of the concepts, resources, and decision

areas the media planner must consider in order to produce accurate predictions of advertising's effects on a target audience." This lack of a framework made the evaluation of many media models in the past difficult and at most, superficial. A general consensus of the normative media selection model, whether it is technically and practically possible or not, is necessary both for the examination of past models and for the sound progress and the development of a more comprehensive model.

There have been only a few researchers who have described the elements that a good comprehensive media selection model should possess. As mentioned in the previous chapter, Rust (1985) suggests that a good media selection model should have the ability to scan many schedules, to estimate audience exposure, and to be comprehensive. This idea is conceptually sound but somewhat ambiguous. To guarantee a schedule's optimality, a model should consider all the possible options. To make its optimality valid, the objective function to be maximized should be the campaign's media objective or its instrumental variable which makes use of exposure distribution essential. A further discussion of exposure distribution will be presented in the next section. However, how comprehensive a model should be still remains unclear here. Aaker and Myers (1975) suggest in a clearer fashion that a media model has to contain three concepts: an objective function, a set of constraints, and a mechanism to select the values of the decision variables that will maximize the objective function within the constraints. To be comprehensive, as they propose, a model should consider five principal components--a simple counting concept, repetition effect, forgetting effect, media-option source effect, and segmentation effect. Despite the fact that their framework could be a good reference for the development of a more comprehensive model, the validity and sufficiency of the five elements which a model should count on and the types of objective functions to be maximized are still debatable.

There is clearly a need to test whether Aaker and Myers' five elements are necessary and sufficient strategic elements to make the model comprehensive.

One way of establishing an ideal comprehensive model of media selection is the development of a framework of media selection that first defines the major concepts of the media selection process and includes all of the important elements within each concept which a media planner must consider when selecting and evaluating the appropriate media vehicles and the number of insertions necessary to convey the advertiser's message to the target audience. As a basic framework, Aaker and Myers' (1975) three-concept framework--objective function, constraints, and comprehensive variables (or, media strategy variables) to affect the value of objective function is sound and practicably plausible.

In sorting out the optimum schedule, the model assigns a value to each alternative in order to compare one schedule to another. The value which the model attempts to maximize is called the objective function. It "provides benchmarks against which the performance of the media schedule can be evaluated and gives a direction to the process of selecting alternative media vehicles" (Aaker and Myers, 1975). Since the optimal schedule is to be selected based on this value, the objective function should represent the criteria that the whole media campaign tries to maximize--media objectives which will eventually accomplish marketing and advertising objectives. It becomes clear that the objective function should reflect some form of media objectives.

In a thorough media planning process, then, the media objectives should be supported by the well-stated <u>media strategies</u>. According to Jugenheimer et al. (1992, p. 12) , a strategy is defined as "a broad course of action recommended to accomplish the stated objectives." In developing strategies, the media planner examines the specific principles of the media function which are likely to achieve both the overall corporate

objectives and the overall media objectives (Scissors and Bumba, 1989). Then, the value of the objective function representing the media goals of the campaign in the media selection model should also somehow reflect these strategy elements to make the model comprehensive. If so, there should be some mechanisms to examine the strategic elements and to link these with the objective function within the model to make the objective function more valid and the model more comprehensive. These strategic elements will be called comprehensive variables under the framework of Aaker and Myers.

Of course, a comprehensive media planning process should consider marketing and advertising situational analyses. These situational variables usually have an impact on the development of objectives and strategies and do not normally directly affect the selection of the media and the vehicles. However, some elements have a direct influence on the selection. Since these do not fall into the domain of advertising media, they may be called <u>constraints</u> in the media selection framework.

Aaker and Myers' three-concept framework fits well into that of the media planning process. As mentioned earlier, however, little attempt has been made to integrate all of the various aspects of the media planning process. It is unclear what elements within each concept in the model should be considered in the media selection process. For example, there are various types of media objectives available in media planning. If the author calls these different components of a concept <u>elements</u>, there certainly has not been any consensus on the essential elements of media objectives, strategies, or other situational variables (i.e., constraints). An effort is needed to integrate these elements for the progress of better media selection research, and this integration seems possible by reviewing and content analyzing the major publications in advertising media planning concerning essential elements of the media planning

process. An objective way to analyze these publications would be to count the number of times each variable is mentioned in the description of the media planning process, assuming that higher frequencies indicate the importance of the variables. This method could be valid in that important elements of the media planning process should be mentioned more often. The description of the essential elements of the media planning process is contained in the description of the everyday process of media buying. Therefore, it is hard to overlook the elements which are important unless the concept is new enough not to have had the chance to be mentioned frequently. To account for these recent elements, the author of this study made some qualitative judgements so that a concept which is new but has not been mentioned frequently could be included in the ideal framework of media selection. Table 1 presents the elements most frequently mentioned by major media planning publications.

Types of Objective Functions

All of the publications analyzed in this study cited *reach*, *frequency*, and *continuity* as possible media objectives (Table 1). Directly related to *reach* and *frequency* were the *gross rating points* (GRPs), a gross measure of audience potential expressed as the sum of the rating points delivered by a particular schedule. This measure is more significant in the tactics of media buying than at the strategic level of planning. It is an important part of the media planner's lexicon and is contained in much of the literature (Table 1).

Table 1
Toward an Ideal Model for Media Selection:
Overview of Literature on Factors Related to Media Selection Models

Criteria	Literature: Scissors & Bumba 1989	Lancaster & Katz 1988	Jugenheimer et al. 1992	Leckenby & Wedding 1982	Aaker et al. 1992	Barban et al. 1985	McGann & Russell 1988
Objective Function							
Reach	*	*	*	*	*	*	*
Effective Reach	*	*			*		
Frequency	*	*	*	*	*	*	*
Gross Rating Points	*	*		*	*	*	*
Continuity	*	*	*	*	*	*	*
Constraints							
Budget	*	*	*	*	*	*	*
Message Factor	*	*	*		*	*	*
Strategic Elements of Advertising Media							
Target Audience	*	*	*	*	*	*	*
Geographical Distribution	*	*	*	*	*	*	*
Time Frame	*	*	*	*	*	*	*
Carryover	*	*	*	*	*		
CPM	*	*	*	*			*
Media Discounts	*	*	*	*	*	*	*
Seasonality	*	*	*			*	*
Competitive Spending Analysis	*	*	*	*			*

Recently, media researchers suggested a relatively new concept, *effective reach*, which is based on the reasoning that optimal exposure frequency appears to be at least three exposures within a purchase cycle (Naples, 1979). Developed from laboratory research studying advertising repetition effects (Joyce, 1984; Naples, 1979; and Ray, Sawyer, & Strong, 1970), this concept suggests that it requires a certain number of exposures for the advertising to have a significant impact on the audience. *Effective reach* attempts to "provide a more accurate and meaningful measure of advertising effects by considering the percent of the target exposed to an advertising schedule some minimum number of times in order for it to have any measurable impact" (Katz, 1988, p. 95). Due to the newness of the concept, only Lancaster & Katz (1988), Scissors & Bumba (1989), and Aaker et al. (1992) have referred to *effective reach* as one of the possible media objectives. However, the concept is becoming important in this domain and can be a possible candidate for the objective function. In fact, recent surveys indicate that over half of all media directors already estimate effective reach in the evaluation of a media schedule (Leckenby & Boyd, 1984b; Leckenby & Kishi, 1982; Lancaster, Pelati, & Cho, 1991; Kreshel, Lancaster, & Toomey, 1985). Thus, the author included this concept as one of the important media objectives despite the low number of times it appeared within these publications.

Continuity concerns "the number of weeks and in what sequence throughout the budgeting year the brand will be advertised" (Leckenby and Wedding, 1982, p. 471). Although this concept is considered one of the most important media objectives (Table 1), the problem of allocation cannot be considered one to be maximized in the media selection model; however, it should be considered the output of the optimal schedule if the model has an ability to handle long-term schedules.

Therefore, this content analysis indicates that the objective function should be in the form of one of the four media objectives which are reach, effective reach, average frequency, or gross rating points (GRPs). Which one of these four should be maximized directly depends on the marketing objectives, the relative importance of each, and the marketing strategies.

Elements of the Constraints

Among the variables that are not in the domain of advertising media but that still make significant impact on the selection of the media, the advertising budget and the creative factors are referred to most frequently (Table 1). Although there are many other non-media variables that a planner should consider in the media planning process (e.g., current sales, characteristics of the brand, or distribution channel characteristics), these elements are usually considered in the formulation of the objective or strategy and are not necessarily related to the selection of the media.

The advertising budget is often set before any media planning process has taken place. When media planning is done in advance, the amount of the advertising budget is determined after considering the types of objectives the campaign is trying to achieve. In any case, considering an advertising budget as one of the media elements is not plausible. The volume of media and the vehicle to be purchased will be decided based on the size of the budget. In such a situation, the objective function will have to be optimized with that constraint in mind.

Creative factors are also important criteria in accomplishing media goals because the quality of copy directly influences the efficiency of the media schedule. Technically, the quality of the message will alter the value of the objective function

which will eventually affect the outcome of the optimum schedule in the media selection model. To evaluate schedules based on message frequency, "planners must have some quantitative appraisal of the communication values of the advertisements in the campaign" (Lancaster and Katz, 1988).

Types of Strategic Elements in Advertising Media Selection

There seems to be a consensus among the reviewed publications concerning what elements to include in the media objectives and in the constraints. However, these publications mention a wide variety of elements that should be included as one of the media strategy variables. This suggestion is made because there are too many strategic elements that a planner might consider to accomplish a goal, and also because the authors in these publications have used different categorization schemes so that one element in one publication could mean two or more elements in the other. For example, while Jugenheimer, Barban, and Turk (1992) simply named the timing of advertising variable "scheduling," Scissors and Bumba (1989) split this concept into "schedule length" and "schedule patterning." The author in this study has tried to find an answer by comparing all the publications and by considering the appropriateness of the terminology in terms of a media selection model. Based on the frequency count and on the appropriateness of the elements in terms of modeling, elements such as target audience, time frame, cost efficiency (i.e., media quantity discounts), geographical distribution, carryover, cost per thousand impressions, seasonality, and competitive spending analysis have been included as strategic elements of advertising media (Table 1). Among these variables, target audience, time frame, and cost efficiency have been considered important strategic elements by all of the reviewed publications. Certainly,

there is a difference between this proposed scheme and Aaker and Myers' five element scheme. As mentioned earlier, Aaker and Myers listed a simple counting concept, repetition effect, forgetting effect, media-option source effect, and segmentation effect as elements that should be considered to make the model comprehensive. While the elements that the present study proposes include the most of Aaker and Myers' components, there are some additional elements the current study recommends such as timing, cost efficiency, seasonality, or geographical distribution.

The media strategy variables can be broken down into four dimensions. *Audience factors* include the interaction of the medium with the viewer or listener such as target audience and demographic considerations. *Scheduling*, a decision of how to allocate an advertising budget over time, is an important criterion in the domain of media objective. A subsequent consideration such as advertising carryover effect also should be included here. Seasonality, which concerns the fluctuation of sales in a certain season, is also an important strategy element. In addition, the necessity of accommodating timing into a model could be an important element in evaluating the comprehensiveness of the model. *Cost efficiency factors* include cost-per-thousand impressions and media quantity discounts. In addition, the analysis of how the other competitors do in their media buying (e.g., *competitive situation analysis*) is also an essential strategic element, although it is very difficult and subjective to incorporate into a model.

Summary -- The Ideal Media Selection Model

A nearly infinite array of advertising, marketing, and media variables can be considered components of a media planning process. If ever possible, a media

selection model which would permit the most thorough media planning incorporate all of these variables. Certainly, this is impossible to do. Our task, then, is to identify the most important factors which should be included in the model. The word "ideal" is defined in terms of the important elements that the model should examine in order to be comprehensive, and an ideal media selection model has been proposed using this operationalization. From the analysis of major media planning publications, the present study has proposed a framework for an ideal media selection model (Figure 2). To make the model comprehensive, it should reflect the thorough media planning process.

To do so, the objective function to be maximized should reflect either one objective or any possible combination of media objectives. Media objectives involve the desired level of reach, effective reach, average frequency, or gross rating points (GRPs). Continuity is also one of the media objective variables, but to consider continuity an objective function is not appropriate. Non-media variables such as advertising budget and message factor also make an impact on the outcome of the solution and should be considered constraint elements.

There are many media strategies that the planner should consider to accomplish the media objectives efficiently and effectively. To make the model comprehensive, there should be some mechanisms to examine the strategic elements and to link these with the objective function. These strategic elements could include target audience, geographical distribution, time frame, carryover, cost-per-thousand impressions, media quantity discounts, seasonality, and competitive spending analysis. Therefore, the conclusion of the present study is that <u>the ideal media selection model should somehow consider all the above mentioned elements</u> (Figure 2).

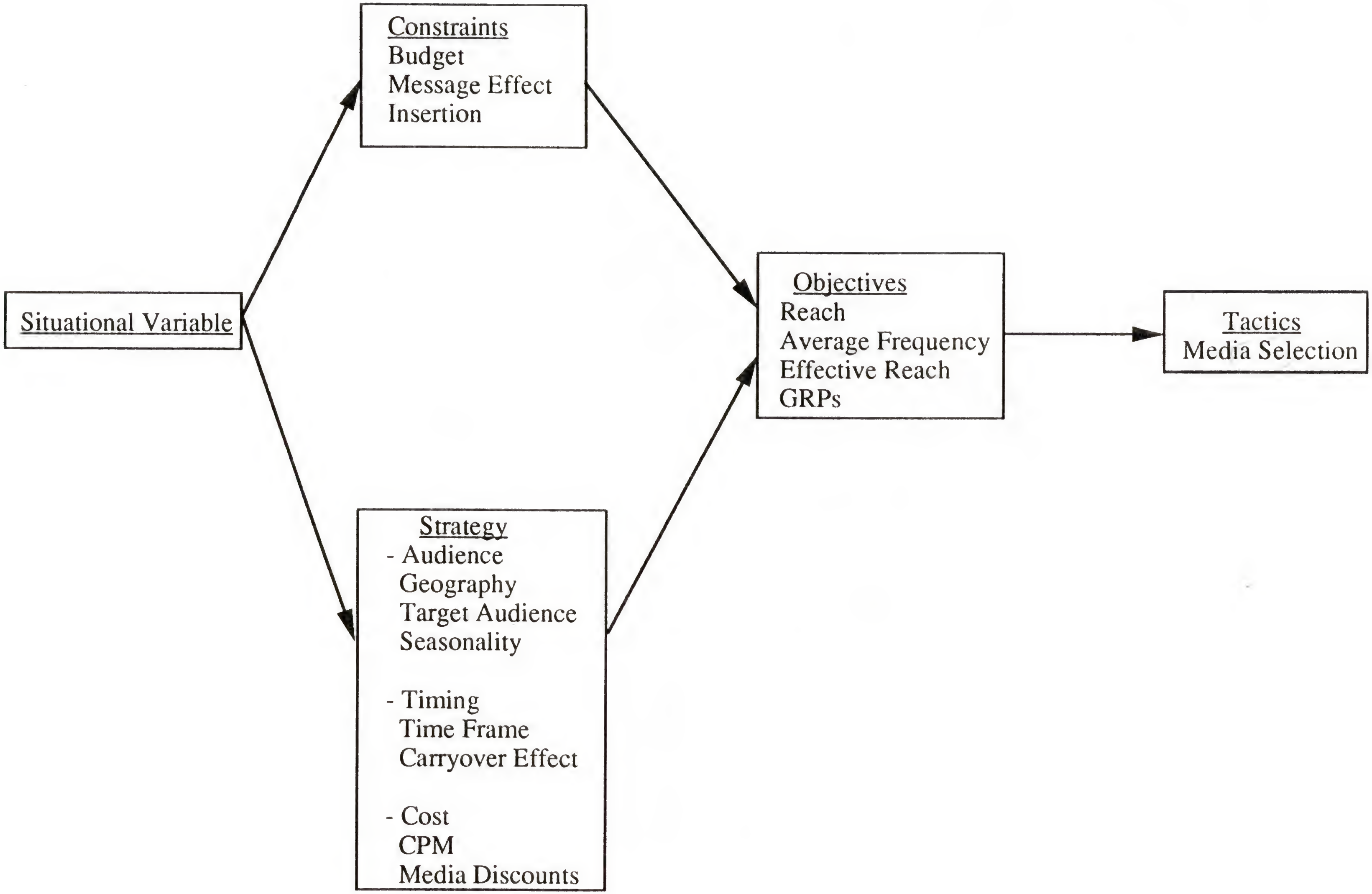

Figure 2. Ideal Media Selection Model

The Evaluation of Past Media Selection Models

Overview

A review of the study on media selection models over the years is presented in the following section. The evaluation of the major media selection models found in past advertising media research is organized according to the major elements of the ideal media selection model proposed in the previous section. These elements include the objective function, constraints, and the strategic elements of advertising media. Some technical variables such as the number of media that a model can handle and the types of searching routines are also included in this evaluation since these variables have a significant impact on the quality of the solution. The major theories underlying the study of advertising carryover effect, the timing of advertising, and media quantity discounts, which are the elements of the media strategy, are also reviewed for the future development of more comprehensive media selection models.

Background

The idea of media selection is not new and has been around for over three decades. In the early 1960s, mathematical models were dominant in this subject. Linear programming models (e.g., Miller & Starr, 1960; Wilson, 1963; Buzzell, 1964; and Stasch, 1965), integer programming models (Zangwill, 1965), dynamic programming models (Little & Lodish, 1965; and Zufryden, 1975), and goal programming models(Charnes et al., 1968) fall into this category.

Another approach was reflected in the simulation model, which tracked the media action of individuals through time (Gensch, 1969; Moran, 1962; and Brown,

1967). These models were capable of accommodating the frequency distribution of exposure and were very comprehensive. Although they try to accommodate as many comprehensive factors as possible, these models lack a mechanism to find the best schedule.

Heuristic models, which use searching heuristics to find an optimum solution, have been popular due to their realism and comprehensiveness. Although these heuristic searching routines are designed to achieve a local maximum, not a global maximum, these routines assume that a local maximum is the same as a global maximum if the decision variables are continuous (Little & Lodish, 1969). These models,which are computationally feasible, examine media vehicle exposure probabilities and values, and vehicle exposure distributions. Furthermore, these models could incorporate qualitative variables such as effective exposure or vehicle appropriateness (Rust, 1989). The most notable of these are MEDIAC, ADMOD, and VIDEAC (Little & Lodish, 1969; Aaker, 1975; and Rust, 1985).

Optimization approaches which find the best impact schedule by evaluating all the possible options, given budget and insertion constraints, have been revived to overcome shortcomings of heuristic approaches in recent days. Although some optimization efforts were made in 1960s and mid-1970s in the development of dynamic and mathematical programming models, the models of this kind have been criticized severely because of their time-consuming procedures and deficient mechanisms to calculate objective functions. However, with the improvement of computer speed, Interactive Market Systems, Inc. (IMS) and Telmar have developed optimization routines. However, these professional media planning computer services for advertisers and advertising agencies have never published their logics or efficiency.

On the academic side, Lancaster (1987, 1988) has developed micro-computer based optimization programs called ADOPT and ADPLAN. These programs, which are capable of incorporating many of the comprehensive media planning concepts such as message exposure distributions, message weights, and effective reach, follow optimization routines and produce single media category optimum solution, in less than 30 minutes.[1]

Using the latest version of ADOPT, The Media Group (1989) from the University of Florida has examined the characteristics of optimum advertising media schedules using message reach(1+), message effective reach(3+), average frequency, and gross rating points (GRPs) in a medium by evaluating virtually all the possible schedules. In evaluating overall impact across criteria in consumer magazines, the Media Group found that the solutions from the optimization of effective reach (3+), average frequency, and gross rating points (GRPs) were nearly identical , but that of reach (1+) led to slightly higher levels of reach (1+) and to substantially less favorable results for all other criteria. In addition, The Media Group showed that the solutions from the optimization approach were significantly better than those from the conventional CPM heuristic (Ch. 4) in consumer magazines. Similar results have been found in other media. Yet, the Media Group has successfully examined the solutions with a single media category where a total number of schedules to be evaluated was several million. Based on the findings from single media optimization, this group could have developed several media heuristics, applied them to mixed media problems, and showed how to generate the optimum schedule without evaluating all the possible

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[1] ADOPT took less than 30 minutes to evaluate 10 million schedules with an IBM 16 MHZ PC machine with a math co-processor.

schedules. This model performed better than the one with conventional heuristic searching methods.

Objective Function

Type

As mentioned in the previous section, the objective function in the model should reflect media objectives. Therefore, the types of object functions adopted by the past major past models have been reviewed with this in mind. Table 2 vividly illustrates the types of objective functions adopted by past major models.

Only the optimization approach models took on some type of pure media objective as their objective function to be maximized (Lancaster, 1987; Lancaster & Katz, 1988; and The Media Group, 1989). Aaker (1975), Zufryden (1975), and Rust (1987) also used weighted media objectives, but the validity of the subjective weighting mechanisms remains in question. The models in the 1960s optimized some forms of marketing variables such as minimization of cost, total market response, or total exposure, based on the linear product of insertion, vehicle rating, and subjective weights on media strategy variables (e.g., Statsch, 1965; Buzzell, 1964; Zangwill, 1965; Gensch, 1969; and Little & Lodish, 1966, 1969). These early models have been severely criticized due to either their unsophisticated method of accessing media impact or the validity of the objective function itself.

In summary, while no one would deny that the media plan should be developed in order to achieve its media goals, not many past media selection models adopted media objectives or their instrumental variables as their objective functions.

Table 2
Overview of Literature on Media Selection Models

Study	Category	Objective Function		Restraints	Number of Media	Searching Routine	Strategic Factors on Media Selection				
		Type	Estimation of E.D.*				Timing & Carryover	Seasonality	Quantity Discounts	Cost Efficiency	Audience
Statsch 1965	Linear Prog.	Min. Cost	No	Total Exposure, Insertion Message	Single	Optimization	No	No	No	Yes	Yes
Buzzell 1964	Linear Prog.	Total Exposure	No	Budget, Insertion Message	Single	Optimization	No	No	No	No	Yes
Zangwill 1965	Decision Prog.	Rated Effectiveness	No	Budget, Insertion	Single	Optimization	No	No	Yes	Yes	Yes
Gensch 1969	Simulation	Judgement	No	Budget Message	Single	None	No	No	Yes	No	Yes
Little & Lodish 1966	Dynamic Prog.	Total Market Response	Yes	Insertion, Budget	Single	Optimization	Yes	Yes	No	No	Yes
Zufryden 1975	Dynamic Prog.	Min. Cost	No	Budget, Reach, Frequency,	Single (Radio)	Optimization	No	No	No	No	Yes

* E. D. refers to Frequency Exposure Distribution.

Table 2 (Continued)

Study	Category	Objective Function		Restraints	Number of Media	Searching Routine	Strategic Factors on Media Selection				
		Type	Estimation of E.D.*				Timing & Carryover	Seasonality	Quantity Discounts	Cost Efficiency	Audience
Little & Lodish 1969	Heuristic Prog.	Total Market Responses	Yes	Budget, Insertion	Mixed	Heuristic	Yes	Yes	Yes	No	Yes
Aaker 1975	Heuristic Prog.	Total Expected Value	Yes	Insertion Message	Mixed	Heuristic	No	No	No	No	Yes
Rust 1987	Heuristic Prog.	Total Expected Value	Yes	Insertion, Budget	Single	Heuristic	No	No	No	Yes	Yes
Lancaster 1987	Optimization	Reach, Effective Reach, CPM, GRPs	Yes	Insertion, Budget Message	Single	Optimization	No	No	No	Yes	Yes
Lancaster 1988	Optimization	Reach, Avg. Frequency, GRPs, CPM	Yes	Insertion, Message	Single	Optimization	No	No	No	Yes	Yes
Media Group 1989	Optimization	Reach, Effective Reach, Avg. Frequency, GRPs	Yes	Insertion, Budget Message	Single & Mixed	Optimization	No	No	No	Yes	Yes

* E. D. refers to Frequency Exposure Distribution.

Reach and frequency estimation

In estimating the value of media objectives, the use of exposure distribution becomes critical since the media planner may deduce reach, frequency, effective reach, and gross rating points (GRPs) of the schedule from the distribution. Increased estimation accuracy in exposure distribution models can be expected to lead to improvement in schedule selection criteria applied either individually or comprehensively in a media selection model.

Considerable research has been conducted on the development of reach/frequency estimation models since Agostini (1961) proposed the method of estimating unduplicated audiences (e.g., Danaher, 1989; Leckenby & Kishi, 1982b; Leckenby & Rice, 1985; Rust & Klompmaker, 1981; and Lancaster & Katz, 1988). These models are broken into two groups: *univariate models* and *multivariate models*. *Multivariate models,* which allow for a multimodal distribution are considered to generate a more accurate estimation. The most notable of these models are the Dirichelet Multinomial Distribution Model (DMD), which permits numerous peaks in the exposure distribution (Rust & Leone, 1984; and Leckenby & Kishi, 1984), and the Log-Linear Model (Danaher, 1988,1989), the modified form of DMD, which permits an unequal number of vehicle insertions in a media schedule. However, these complex models require more data manipulation and more computation time. An attempt to incorporate these models into the media selection model is not desirable because parsimony is so important and because of the complexities involved in the process of producing an optimal schedule. Moreover, it is "unlikely for even a highly sophisticated model such as the DMD model to provide a high level of accurate reach/frequency estimation" (Ju et al., 1990).

Univariate models, which only allow for a bimodal distribution, have gained great popularity in practice because they have the advantage of being relatively elegant, simple, and reasonably accurate. The most popular univariate model, the Beta Binomial Distribution model (BBD), is a composite of both *beta distribution* and *binomial distribution models*. The beta distribution model evaluates "the number of different ways that the target members can be exposed to that schedule" (Katz,1988, p. 98) and the binomial distribution model determines "the probability of exposure to that schedule" (Katz, 1988, p. 98). At least two recent surveys have shown that BBD is the most heavily used model in the advertising industry (Kreshel, Lancaster, & Toomey, 1985; and Leckenby, & Kishi, 1982a). Other forms of univariate models include the binomial distribution model, which has been criticized for being less accurate (Aaker, 1975), Hofman's geometric distribution model (HGD), a combination of Hofman's reach formula with the geometric distribution, which is not accurate in the early exposures (Kishi & Leckenby, 1981), and Hofman's beta binomial distribution model (DBBD), which is a modified version of BBD (Leckenby, & Boyd, 1984a). The univariate models possess the advantage of parsimony, an important characteristic of theory development.

Most reach/frequency estimation models require vehicle rating and duplication as model input. However, some univariate models which do not require duplication gained popularity due to their parsimony, which is a crucial component of theoretical development, and their relative accuracy (Lancaster & Martin, 1988; Lancaster & Katz, 1988; Ju & Leckenby, 1989; Leckenby & Rice, 1985; and Headen et al., 1976). The duplication data in these models can be estimated in one of three ways: by the method of means and zeros (Leckenby & Rice, 1985), by the use of regression analysis (Lancaster & Martin, 1988; Lancaster & Katz, 1988; and Headen et al., 1976), or by

the use of Poisson binomial distribution, which does not require duplication data (Ju & Leckenby, 1989). Although these limited information models may give a less accurate estimation than the full information models, the limited information models can be preferable when no duplication data is available or when the parsimony of the process is important since the models are acceptably accurate.

Concerning the application to media selection models, most models, except those that use linear programming, have tried to estimate exposure distributions either by simulation (Gensch, 1969; and Little & Lodish, 1966, 1969) or by the univariate models mentioned in the previous section (Aaker, 1975; Rust, 1987; Lancaster, 1987; Lancaster & Katz, 1988; and The Media Group, 1989). Among the estimation methods adopted, beta binomial distribution model is the most sophisticated and accurate method and recently-developed media selection models have started to apply this method (Rust, 1987; Lancaster, 1987; Lancaster & Katz, 1988; and The Media Group ,1989).

In the application of media selection models, the reach and frequency estimation model, which has simpler algorithm while producing reasonably accurate results, should be preferable. For that reason, multivariate models such as DMD or the log-linear model, which requires a complex computation process, do not seem to be plausible. Among various types of univariate models, the beta binomial distribution model is the most popular model in practice and its accuracy seems to be well above the acceptance level. However, there is no single answer to which types of BBD models the media selection models should use. While the BBD with limited information (BBD-L) model is simpler than the BBD with full information model (BBD-F), this simplicity does not necessarily mean that the former will obtain the solution faster than the latter. Since the BBD-L model does not require duplication data, it is more convenient to the user and useful when such data is not readily available. On the other hand, the BBD-F

model should be more accurate than the BBD-L model. Therefore, a decision of which specific estimation method will be used should be made after considering the types of media which the model is trying to estimate and the other elements that are linked with the objective function within the model.

Timing of advertising

When the media selection model has the ability to produce a long-term optimum schedule, the problem of how to allocate an advertising budget longitudinally is not a serious concern because the solution itself can properly answer when and how much to advertise. However, few models could successfully handle this problem, due to its complexity. Only Little and Lodish (1966 and 1969) designed a model which could accommodate long-term schedules, but their mechanisms were not satisfactory in that the objective function they used was linear. Rather, the question of timing of advertising to maximize the impact has been a heavily studied topic in the behavior research in advertising, but not in media selection research, since behavioral approach is considered to be an easier way to handle this problem.

In this research domain, most past research has focused on the evaluation of the effectiveness of continuous versus pulsing schedules. The evidence supports both scheduling patterns, although studies supporting pulsing scheduling seem to be prevalent. Katz (1980) conducted a field experiment with two groups, one with continuous and the other with pulsing scheduling, and found that pulsing scheduling performed better when measured according to the unaided recall of a product. Learning and forgetting, as Katz explains, are the key factors in recall, and intense scheduling in the early period is necessary for initial learning. After an initial learning period, reduced effort may be enough to sustain the advertising effects.

Simon (1982) applied the economic approach and drew the same conclusion. Using the GLS procedure, he developed the advertising - sales response function and eventually the long-term profit function. Three different types of schedules (continuous, altering pulsation, and repeat pulsation) were tested in terms of long-term profit. Results show that altering pulsation with a pulse every other month yielded the best performance.

Strong (1977) tested seasonality effects in conjunction with timing effects. To do so, he developed a computer model which allows a decision maker to weight the seasonality. Using data from field experiments, he measured unaided recall, which was the objective function needed to test the impact. Finally, the model evaluated a limited number of schedules and selected the best one. Results supported the pulsing strategy. Yet, specific timing was altered when seasonality was considered. Other evidence includes studies by Ackoff and Emshoff, 1975, Haley, 1977, and Rao and Miller, 1975.

On the other hand, Zielske (1959) in his field experiment with two schedules -- pulsing and continuous -- measured unaided recall to test the impact of each schedule. The results supported the continuous schedule. After having faced with a large number of counter-arguments in the 1970s, Zielske and Henry (1980) replicated the 1959 study. They first developed the unaided recall response function and explored several scheduling patterns using this function. Results showed inconclusive evidence. Later, they concluded that different ways of allocating the same number of television rating points over time produce radically different patterns of advertising recall, and that the choice of scheduling could depend on the specific situation.

Constraints

Vehicle insertion constraints

In addition to the advertising budget and the creative factors which are non-media variables, an additional constraint shown in the literature of the selection of media is insertion constraint. Vehicle insertion constraint refers to the maximum number of insertions that a program will examine for a certain vehicle in the optimization process. This is a technical constraint which can be decided either by the vehicle itself (for example, a maximum insertion for monthly magazines in a month is one) or by the media planner, since the maximum number of insertions along with the number of vehicles in the database will constitute the size of the problem. All of the past media selection models had insertion constraints (Table 2).

Advertising budget

Table 2 shows that all past media selection models had budget constraints, except ADMOD (Aaker, 1975), a model which tries to recommend an advertising budget based on the efficiency of the schedule. On the other hand, some models have a lower budget limit, which accounts for this variation in total schedule cost (Lancaster, 1987; Lancaster & Katz, 1988; and The Media Group, 1989). An advantage to having a lower budget limit is the reduction in computer time required in obtaining a solution. This lower budget limit makes models eliminate schedules on the basis of cost alone, without running into an extensive reach and frequency estimation procedure for each option.

Message effect

As Kreshel et al. (1985, p. 33) note, "Many media planners seem to continue to assume that audiences are automatically exposed to advertisements once they are exposed to vehicles." Planners should be careful to acknowledge this assumption for two important reasons: 1) their main interest should be to obtain some measure of performance from the exposure to the advertisements, and 2) the estimation of the reach and frequency with vehicle rating will not lead to the message reach and frequency without having a proper mechanism to adjust this. A recent survey revealed that only one-third of all media executives noted that their agency quantitatively considers media vehicle audiences (Lancaster, Kreshel, & Harris, 1986).

To estimate properly a scheduling impact in terms of the message effect, media selection models should have some type of mechanism to adjust this effect. As Table 2 shows, a great number of media selection models have an option to consider message effect, due to its importance in the media selection process, and most of these are linear programming models (Stasch, 1965; and Buzzell, 1964) and simulation models (Gensch, 1969). These three models have adopted a single weighting method, and the size of the weight has been adjusted depending on the size of the message. Recently, optimization approach models have tried to estimate the message exposure distribution, which concerns a proportion of people who saw the message to each frequency level rather than those who saw the vehicle, in order to access a more sophisticated advertising impact (Lancaster, 1987; Lancaster & Katz, 1988; and The Media Group, 1989).

Number of Media

Although advertising campaigns for most major consumer goods brands involve more than one media category, only a few media selection models have the capability of evaluating plans with multiple media (Little & Lodish, 1969; Aaker, 1975; and The Media Group, 1989). This evaluation is difficult because of the complexity of the problem and of the difficulty involved in combining schedules with different media. In fact, only The Media Group (1989) used a technique that combined exposure distributions of several different media to evaluate the overall media weight of an entire campaign, in addition to individual media categories. Most media selection models assume the budget allocation in each media is set before the media plan, so that it is only necessary to optimize the schedule within a specific medium.

Searching Routine

To recommend an advertising schedule, the media selection models have their own way of searching for the best schedule. Most previous media selection models have opted for the optimization approach, which evaluates all the possible options before producing the optimum solution (e.g., Statsch, 1965; Buzzell, 1964; Zangwill, 1965; Little & Lodish, 1966; Zufryden, 1975; Lancaster, 1987 and 1988; and The Media Group, 1989).

The models from the simulation approach, on the other hand, did not have a searching mechanism while they put more emphasis on accommodating more comprehensive variables. Therefore, while the estimation of the scheduling impact from this approach is considered to be very reliable, it has been the user's responsibility to find the optimum combination of the schedule.

Still, some models have tried to relieve the complexities of media selection by developing a way to find a reasonable solution without evaluating all possible options. This method is called the *heuristic searching approach* (Little & Lodish, 1969; Aaker, 1975; and Rust, 1987). The reasoning behind the use of heuristic searching is that this method will find a local maximum solution which will be a global maximum if the decision variables are continuous (Little & Lodish, 1969). Considering the fact that the problem of media selection is such a challenging task, developing heuristics that will lead the model to an optimal solution is a plausible way to reduce the problem size, if the heuristics are proven to perform properly. However, all of the previous heuristics except the one developed by The Media Group (1989) have not been developed based on the analysis of optimal solutions. Instead, the heuristics in the past have been developed based on the model builder's reasoning or borrowed from other disciplines which handle similar problems. As mentioned in the early part of this chapter, The Media Group (1988) showed that the solutions from the optimization approach were significantly better than those from the conventional CPM heuristic, based on the comparisons of the solutions from both approaches. This finding certainly indicates that the searching routines from the heuristic searching approach do not function properly in finding the best schedule. Therefore, <u>unless there is a guaranteed mechanism to find a solution that is close to the optimum, the optimization approach should be recommended</u>.

Strategic Factors of Media Selection

Timing and carryover

When the model accommodates long-term planning rather than monthly planning as a typical media plan does, this new dimension should lead not only to a more realistic model but also to an increased problem size and additional factors to consider. Long-term planning is not just an aggregation of monthly plans. To make this problem reasonable, the model should consider factors such as carryover effects, since the advertising in a certain month should have some types of impact on subsequent months. The model cannot be valid without considering this effect. Since carryover effect on media usually refers to the amount of recall or exposure carried over through the subsequent period rather than to sales, this carryover effect of recall is often called decay in recall in behavioral research.

Only Little and Lodish (1966, and 1969) have tried to accommodate this timing dimension, coupled with advertising carryover effect, because of its importance in the media planning process. Considering the reasoning that the effect of advertising wears off because of forgetting, they hypothesized that in the absence of new input, the exposure level decreases by a constant fraction during each time period. This constant, called *carryover rate,* ranges from zero to one. Using the geometric lag equation, they showed how to employ carryover effect. To get an empirical value of carryover rate, they suggested a review of the studies on decay in exposure from the social psychological approach.

Studies on carryover effect

Introduction. *How long does carryover effect last?* This simple question has been one of prime importance to many marketing, advertising, economic, and social

psychological researchers, and the subject concerning this question has been termed *carryover effect*. Carryover effect, by definition, implies that an effect lasts beyond a single time period.

In econometric terms, carryover effect is a type of lagged variable between independent variables and dependent variables which is designed to better explain the dependent variable. Therefore, there can be various types of carryover effect. In fact, the studies of carryover effect in advertising research have shown a wide variety of response measures (i.e., dependent variables) such as sales, recall, recognition, attitude, or purchase intent. The two most flourishing disciplines in the study of carryover effect are economics and social psychology. Their focuses have been drastically different from each other, although researchers from both fields have studied the same phenomenon for more than four decades.

While researchers from economics have focused both on a functional relationship between advertising and sales and on the duration of carryover effect which focuses on the time frame and carryover rate (e.g., de Kluyver and Brodie, 1987; Windal and Weiss, 1980; and Aaker et al., 1982), researchers from social psychology have examined forgetting or decay in recall in cognitive processes and have placed more emphasis on the theoretical relationship between exposure and its decay, the factors affecting the forgetting of advertising, and the relationship between repetition and rate of cognitive response (e.g., Laband, 1989; Singh et al., 1988; and Belch, 1982). The empirical evidence found in the past timing of advertising studies is organized according to the major elements within this subject, and the studies from both approaches are reviewed and presented together where appropriate. The major elements in the timing of advertising include the functional relationship, time frame and carryover rate, the factors affecting carryover effect, and advertising repetition effects.

Functional relationship. In the evaluation of a long-term media plan, the major concern in relation to carryover effect would be how to deal with the carryover of the media impact (i.e., exposure) in the previous time period. This has been termed "decay in recall" and has been studied in the social psychological discipline.

For over a century, the studies in social psychology have focused mostly on providing information on what processes underlie carryover effect, especially within individuals. Among the first researchers who studied learning and memory, Ebbinghaus (1885), using a list of nonsense syllables as test stimuli, suggested that the rate of carryover geometrically decreases as time moves on. This negatively accelerated forgetting curve theory has drawn a great deal of attention, and Ebbinghaus' findings have been replicated or improved ever since (e.g., Postman and Rau, 1957; and Greenberg & Garfinkel, 1962). For example, Craig et al. (1976) not only confirmed that the forgetting curve accelerates negatively, but also found that the rate of decay could vary depending on the product familiarity. Other evidence such as those produced by Simmons (1965) also supported this curve shape. Although a predominant number of studies conducted on this subject support the negatively accelerated forgetting curve, the researchers in this domain have failed to suggest any type of regression function for this phenomenon since their research format (i.e., experimental design) could not give sufficient data of this kind.

This failure may cause a problem in the application of carryover into the media selection model since the main focus in the model would be how to deal with carryover effect in conjunction with the objective function to be maximized. The studies from the social psychological domain have only shown that the rate of carryover in recall geometrically decreases. Fortunately, the answer to the question of how to formulate

the proper equation of decay in recall could be obtained from the studies in economics. The researchers from the economic discipline have studied the regressional relationship on the carryover effect although the studies of carryover in economics have always been conducted in an effort to understand more fully the structure of the advertising and sales relationship, not the structure of exposure and the size of the decay rate. Yet, the various forms of equations proposed here could also be useful in applying decay in recall into the media selection model, once the rate of carryover in exposure has been determined. Here, the effects have been measured using a variety of distributed-lag models that provide information about both the magnitude of such effects and their duration. Various types of advertising carryover effect models have been introduced and are reviewed herein.

According to Barnes and Wildt (1980), most models basically fall into two categories depending on their underlying assumptions: *explicit models* and *implicit models*. *Explicit models* are based on a set of specific assumptions regarding the nature of the carryover process. Such assumptions are that the effect of a one marketing-mix variable is distributed over several time periods and the underlying response is linear. The geometric lag model and geometric lag autoregressive model belong to this group (e.g., Aaker et al., 1982; Rao & Miller, 1975; Lambin, 1972; and Bass & Clarke, 1972). *Implicit models* postulate that sales or market share in the current period are functionally dependent on the previous period's sales or market share, thus advertising and the other marketing-mix variables exert a cumulative effect. The partial adjustment model, partial adjustment autoregressive model, and current effect autoregressive model are within this category (e.g., Weiss & Windal, 1980; Beckwith, 1972; and Schultz, 1971).

Certainly, there is no single answer for which type of regressional equation one should use to employ the effects of carryover. The choice of a specific type of model should be decided based on the underlying assumption of the particular problem. Yet, the Koyck model (1954), which is a form of geometric lag model, has been the most commonly used carryover effect model in advertising-sales studies. Little and Lodish (1966 and 1969) who applied the carryover effect into their media selection models, also used this type of the regression equation.

Time frame. In the application of carryover effect into the media selection model, the decision of the unit of time period should also be an important concern. Yet, this seemingly simple decision should be made only after several considerations. First of all, the data interval bias should be considered. The subject of data interval bias concerns the fact that the analyses of advertising carryover may pose a bias if the cumulative advertising effect lasts for a shorter period of time than that of the data interval. In a survey of 69 advertising carryover studies which had a wide variety of data intervals ranging from a week to a year, Clarke (1976) explored this subject. He thought "the consistent estimation with different data intervals would require that the size of the carryover should be larger for shorter data intervals than for longer ones if there is not any data interval bias among these studies" (Clarke, 1976, p. 351). Yet, he could not find any consistencies among these studies. Using the current effects model, which hypothesizes that it is of a shorter duration than the data interval to have a cumulative effect attributable to advertising, he analyzed those 69 studies. He found that studies with a yearly data interval showed bias. In addition, he also found that weekly results are probably biased downwards because the purchase cycle is longer than the data interval. Finally, he concluded that the duration of advertising carryover

occurs within three to four months of the advertising so that the monthly studies seemed to be more consistent with the data.

In the decision of time frame in the media selection model, other considerations such as the most popular basic unit of planning among media planners and the types of objective functions a model evaluates should also be helpful. A recent survey of media directors revealed that the monthly time frame is indeed the most commonly used unit (Lancaster et al., 1986). For example, in planning for the consumer magazines, 50 percent of the media directors used the monthly time frame. In addition, if a planner evaluates the media plan based on cognitive criteria, the estimation of a schedule impact may not be a true evaluation of the criteria if the plan has a period longer than a month. This is due to the existence of decay in recall within the time frame unit (Lancaster et al., 1986). Considering the fact that most media planning researchers recommend reach, average frequency, effective reach, or gross rating points (GRPs) for media objectives (Table 1, p. 20), these quarterly or yearly time frames may not be reasonable time units in the media selection model. Considering the various perspectives on the time frame, the empirical findings seem to support the <u>monthly time frame</u> for the best unit in the media selection models.

<u>The size of the carryover rate.</u> Another question related to carryover effect on advertising exposure concerns the amount of the advertising exposure that will be carried over to the subsequent time period. Certainly, the size of the carryover effect is affected by the time period unit selected by the planner (Clarke, 1976). However, even after the time period unit has been decided, the amount of exposure carried over will vary depending on various factors. This phenomenon has been revealed studies of the carryover effect on cognitive criteria.

Studying factors that affect the rate of learning, Laband (1989), in his television advertisement content analysis, found that the intensity of information could affect the rate of decay. Various factors such as meaningfulness of the stimuli (Underwood & Schultz, 1967), similarity of items (Underwood & Ekstrand, 1967), the size of the advertising message (Strong, 1914), and the level of original learning itself (Underwood, 1964) have also made significant effects in the rate of recall. These findings illustrate that the amount of the advertising exposure carried over will not be a constant figure and will vary mostly depending on message factors in advertising in the media selection models.

Advertising repetition effects. Not only do various creative factors such as the meaningfulness of the message, or the size of the message affect the amount of exposure carried over, but also the amount of exposure also affects the size of the carryover rates. For instance, a group of people who have been exposed to the message three times will certainly have a higher chance of remembering that message through the subsequent period than those who have been exposed to the message only once. This effect has been termed *advertising repetition effect.* Since recent media selection models have started to evaluate the exposure distributions of the advertising frequency for better estimation of the impact, and the various rates of the carryover have to be applied to each exposure frequency when the carryover effect on advertising exposure is considered, a question of how the size of the carryover rates will change according to the amount of the repetition merits special concern.

Concerning the repetition and the rate of cognitive response, most research findings seem to support a positive relationship. Rethans et al. (1986), in their experimental study of receiver knowledge, commercial length, and repetition (one,

three, or five), found that familiarity with and recall of a novel television commercial increase as exposure frequency increases, particularly for the individuals exposed to the longer version of the experimental commercial. Calder and Sternthal (1980) measured cognitive responses after commercials for two products, one familiar and one unfamiliar to the participants. They found that increased frequency of exposure led primarily to more positive thoughts for the unfamiliar product and to an increase in negative thoughts for the well-known product. McCullough and Ostrom (1974) examined the effects of repeated exposure by having subjects view five similar advertisements that used the same basic appeal, but that differed in the order and phrasing of the message arguments. Cognitive responses were measured immediately after each exposure. They found that repetition resulted in a significant positive effect on cognitive response activity as subjects listed more positive thoughts and fewer negative thoughts with repeated exposures. Belch (1982) also found support of a positive relationship between cognitive response and repetition in an experiment of cognitive response and message acceptance. Other evidence of this positive relationship includes studies by Appel, 1971, Grass & Wallace, 1969, Ray & Sawyer, 1971, Strong, 1916, Obermiller, 1985, and Hitchon et al., 1988. Since the studies in this stream adopted the experimental approach with various treatments, none of the above studies have been successful in suggesting any regression equation which can be helpful in applying this effect into the media selection model. Yet, the dominant number of studies reported that the relationship between the frequency of exposure and its corresponding amount of recall draws convex shapes depicting perceptions of diminishing returns in relation to advertising frequency (Appel, 1971, Grass & Wallace, 1969, Ray & Sawyer, 1971, Strong, 1916, Obermiller, 1985, and Hitchon et al., 1988).

Recently, Lancaster, Pelati, & Cho (1991) conducted a national survey among leading media directors to see how they perceive advertising repetition effects. In this survey, the planners were asked to describe the types of communication goals they used for the evaluation of their media schedule and to draw a function to show the perceived communication effect probabilities provided for each frequency level. Over 90 percent of the media planners indicated some type of cognitive communication goals. For the response function shape, more than 80 percent of the planners reported that they thought the relationships produced a convex function. The graphs were, then, aggregated across a variety of reported communication effects and media schedule characteristics. The result was clearly consistent with the convex response functions found in most previous studies. The results from this survey indicate that media planners in practice perceive that advertising repetition effects have a convex response function shape.

Seasonality

Although not every product has seasonal differences in sales, advertisers of certain products need to consider seasonality if the model handles the timing of advertising. This consideration is necessary because the impact of the advertising in a certain season is expected to be different from the impact in another season, despite the same amount of advertising due to the differences in the audience's selective attention process. However, no reliable way of weighting advertising impact considering seasonal differences in sales has been found.

Among the past media selection models, only Little and Lodish (1966 and 1969) have accommodated this variable by using a weight generated from the calculation of the proportion of sales in each month used to decrease or increase the

impact of each month's advertising. The validity of this proportion of sales in seasonality weighting still remains in question, although there are no better alternatives available in the application of the seasonal disparity problem. Other models could not accommodate this variable since they are static.

Media quantity discounts

There seems to be a general acknowledgement in the past literature on the importance of quantity discounts in media selection (e.g., Jugenheimer et al., 1992, pp. 268-82; and Scissors and Surmanek, 1982, p. 201). Scissors and Surmanek (1982) emphasized the importance of examining media quantity discounts in media planning by saying that:

> ... sometimes the value of a medium is directly affected by the nature of the discounts that it offers. If a number of ads are planned for a calendar year in several vehicles that are otherwise about equal, that vehicle offering a substantial discount may represent the best value of all. However, it would seem obvious that discounts rank relatively low on the scale of various criteria (Scissors & Surmanek, 1982, p. 201).

However, only a few studies empirically support the importance of the evaluation of the media quantity discounts in media planning. Concerning discount effects on schedule optimality, Kaplan and Shocker (1971) hypothesized that the existence of media quantity discounts introduced difficulties that would prohibit a purely mathematical programming approach from reaching an optimal solution even with a non-linear effective function. In the example presented, the presence of media quantity discounts results in the incremental heuristic search finding a solution schedule with effectiveness 12 percent below the maximum, due to its failure to see beyond the initial purchase of the first vehicle.

Despite the general consensus on the importance of quantity discounts on media, an application of this variable into media selection models has been rare. Within the author's exploration on literature, only MEDIAC (Little & Lodish, 1969) has applied an iterative procedure for handling media quantity discounts which initially solve the problem without applying media quantity discounts. MEDIAC then eliminates options which do not appear, adjusts the cost for the options being used, and finally solves the problem. This lack of application occurs due to the very complex structure of media quantity discounts so that it is very hard to incorporate into a model; yet the neglect of media discounts may jeopardize the optimality of the solution.

Cost efficiency

Cost efficiency is usually considered in the phase of the development of the database, which constitutes the most efficient vehicles for a brand. In the media selection process, cost efficiency may not play a part in selecting vehicles and insertions unless specified to do so. The model is designed to optimize a certain objective function, not cost efficiency, and will evaluate all the possible options. Some media selection models have an option of optimizing cost-per-thousand impressions (CPM) to guarantee cost efficiency (Lancaster, 1987; and Lancaster & Katz, 1988); however, cost efficiency is usually highest within the lower advertising budget. Optimizing the schedule based on CPM may often produce a schedule that is far below the recommended advertising budget since larger advertising volume will usually produce lower cost efficiency. If other factors are held constant, the schedule with better cost efficiency will always be preferred. However, it seems out of question to choose a lower objective value (e.g., reach) schedule with better cost efficiency instead of choosing an optimum objective value schedule with worse cost efficiency where the

media objective is to maximize the reach. Many media selection models produce the cost efficiency figures of the optimal schedule in their output (Statsch, 1965; Zangwill, 1965; Rust, 1987; Lancaster, 1987; Lancaster & Katz, 1988; and The Media Group, 1989).

Audience factors

As shown in Table 2, all the media selection models had a mechanism to examine this factor. Usually, the target audience is considered in the data input stage like cost efficiency by inputting the audience ratings in terms of the brand's target instead of the typical adult population (e.g., Lancaster, 1987 and 1988; and The Media Group, 1989). By considering the target audience in this manner, the planner is able to select the vehicle that is most efficient to the brand. There are various measurement services that media planners rely on for data on specific target audiences, which they will then use to help produce more precise estimates of advertising's effects on those targets. These services include Arbitron, A.C. Nielsen index, Simmons Market Research Bureau (SMRB), and Scarborough.

Some media selection models have also considered demographic disparities of the target audience (Rust, 1987; Little & Lodish, 1966, 1969; and Zangwill, 1965). To consider these disparities, Rust (1987) and Little & Lodish (1966) first estimated each segment's objective function value. Following this step, the segment values were added together to form a global value of objective function after applying a proportional weight to each segment value to consider geographical flexibilities. On the other hand, Zangwill (1965) considered geographical flexibilities by setting a series of constraints in each segments.

CHAPTER 3
THE VALUE OF A COMPREHENSIVE MEDIA SELECTION MODEL AND THE SCOPE OF THE STUDY

The Value of a Comprehensive Media Selection Model

The review of the literature presented in Chapter 2 clearly shows that the media selection model should reflect the comprehensive media planning process, and the reasons for this have been presented many times throughout this report. Yet, the literature review reveals that virtually no comprehensive media selection modeling framework is available in this field. Accordingly, a comprehensive media selection model which reflects the thorough media planning process has been proposed in the earlier section of Chapter 2 (Figure 2, p. 26). Developing a media selection model framework is very important since the framework can be a measure to evaluate the past models both to give an idea of their performance and to reveal a direction for the future development of the media selection model. In fact, any of the past studies in media selection models have not successfully defended their use of certain media planning variables or their negligence of other variables for the evaluation of the schedule. In most cases, the studies have put more efforts into describing the procedures of employing those variables. In addition, there were no consistencies found among the past models in terms of the types of the variables and the objective functions they have employed for the evaluation of the schedule (Table 2, pp. 31-32). This lack of consistency certainly indicates that the model builders may have either different

opinions or no opinions on where the model should go.

The review of literature also shows that none of the past models have satisfied all the criteria suggested in the ideal media selection model. This ineffectiveness is not surprising when the unavailability of any comprehensive media selection modeling framework to model builders and the numerous complexities involved in the media selection process is considered. Yet, some of the past media selection models have been close to the comprehensive media selection model proposed in this study.

In terms of the number of criteria examined, MEDIAC (Little & Lodish, 1969) is the most comprehensive. The only criterion ignored by MEDIAC is the cost efficiency of the schedule. In fact, this model is the only media selection model which realistically evaluated the long-term schedule with carryover effect and seasonality. Yet, MEDIAC neither adopted any reach and frequency estimation method such as the beta binomial model nor evaluated all the possible options to produce the optimal schedule. These unsophisticated estimation methods and heuristics may jeopardize the validity of the optimal solution from MEDIAC.

On the other hand, ADOPT (Lancaster, 1987; and The Media Group, 1989), the most sophisticated model, estimates the exposure distribution of a schedule using the beta binomial distribution method, applies message response function to consider creative factors, combines the exposure distributions of different media to produce the combined value of the objective function using a *random combination method* which has a proven relative accuracy (Lancaster & Katz, 1988), and still evaluates all the possible options. However, ADOPT can be vulnerable because the model is static and ignores some strategic factors such as media quantity discounts.

Verifying the Ideal Media Selection Model

At a moment when a comprehensive media selection model has been specified, the next step that the present study should pursue is to verify the model. Since the ideal media selection model has yet to be tested, the superiority of the suggested model and the impact of each element in the model on the estimation of the schedule or on the selection of the vehicles are still unknown. This verification process is important because it enables us to know why the model and each element in the model are important and how each element performs in the media selection process. This test also enables us to eliminate some elements which do not make a significant impact on the process. In addition, the parsimony of the model is another important task to model builders due to the complexities. If every variable is important, eliminating some factors to make the model practical may jeopardize the validity of the optimal solution. If some important variables do not make a significant impact on the solution, they can be ignored in the process of optimization.

More specifically, the present study will verify the impact of each element in two ways: the impact on the value of the objective function and the impact on the selection of vehicles and their insertions. This study tries to verify whether each element in the model is significant enough to affect the outcome of the recommended optimum schedule. Is the recommended solution from a model that examines an element significantly different from the solution suggested from a model that does not examine an element? In addition, does such difference in vehicle selections indeed lead to the difference in the estimated media impacts between the two solutions? These are the basic two questions the author tries to answer in this verification process. In other words, while the test of an impact on the selection of vehicle will verify whether the solutions from a model with an element are indeed different from those from a model

without an element, the test for the value of the estimated media impact (i.e. objective function) will provide the information of whether these two different solutions will indeed generate different media impacts. Even if the accommodation of an element in the model makes the vehicle selections in the optimum solutions different, there will be no need to consider that element in the optimization model if this accommodation does not make the estimated media impact of the optimum solution different.

Anyway, if an element will indeed make a significant impact on the solution, an optimization analysis from a model without an element cannot obtain any validity. On the other hand, if the use of an element will not make any difference in the selection of the vehicle, model builders will be able to eliminate that element in the optimization analysis so as to reduce the computation time.

The remainder of this study will be devoted to the verification of the model proposed in this study. This study will help to reevaluate the ever-challenging media selection problem, to understand the media selection process accurately, and to suggest the direction the model should go.

The Scope of This Study

It may be ideal to verify the significance of the elements in a model which can handle a multi-media and long-term plan, to evaluate all possible options, and to examine all the strategic elements. In the analysis stage, a researcher still has to test each element in every combination of mixed-media situations. However, to do so would certainly require a huge number of researchers and a large amount of money and time. More importantly, in a situation where little past research has been conducted, where the knowledge of the subject is limited, and where the demands of the

optimization process are time consuming, the simultaneous testing of all of these options is never feasible. The present study does not intend to achieve this life-long challenging task all at once. In fact, this study starts with a very simple problem, single media long-term optimization. This problem is simple in comparison to the multiple-media selection process, but may never be simple considering the absolute problem size itself. There is no need to reemphasize how complex this problem could be.

Within the single media framework, many different situations may be encountered by an advertiser. One brand has a seasonality in sales, while another has a geographical imbalance. If one decides to incorporate all these differences in testing the framework, he/she has to handle every different seasonal and geographical situation in the analysis, which could require huge resources. In addition, these seasonal and geographical variations do not usually require more computation time since a typical way of accommodating these variations would be to apply a portion of weight to decrease or increase the impact of each month. Since one of the main objectives of achieving parsimony of the model is to resolve the problem complexity, variables such as seasonality and geographical distribution which will not affect the computation time but which will require large additional analyses to verify the impact will be left for future research. Therefore, the present study will focus on a single media long-term optimization model for a national and typical brand which does not have seasonality and geographic variation.

The Decision to Use Consumer Magazines

To assess the significance and impact of each element of the proposed model in the media selection, a more specific focus is needed. While one would ultimately wish

to be able to verify the framework with all major media categories (consumer, business, and agricultural magazines, national and local newspapers, network, spot, and cable television, network and spot radio, outdoor, and direct mail), there is no doubt the verification with all major media categories would require time, money, and human resources. Having accepted the fact that one cannot test all media simultaneously, one has to select a media category on which to focus. As a pioneering study in this area, the present study will focus on the medium which is most typical. Here, consumer magazines are selected for the analysis of testing the proposed model. While other media categories such as broadcast and cable network, spot and local television and radio, national and local newspapers and supplements, or outdoor could also be good candidates for single medium long-term optimization, the verifications with other media will be left for future study.

In a technical manner, consumer magazines are preferred to other media categories for the present study because this medium self-restricts the maximum monthly allowable vehicle insertions to one insertion in monthly magazines and to four insertions in weekly magazines. Due to the size of the problem, if this study has to test the framework with smaller databases, the use of consumer magazines could make the databases more realistic.

Over 11,000 magazines are published, ranging in editorial content from general editorial to highly specialized classifications. *Standard Rate & Data Service* lists 67 classification groups in all. This wide variety of specialized magazines permits the advertiser to reach both very general and highly selected audiences.

Magazine advertising has been growing continuously each year, representing about a five percent increase rate (Coen, 1986). In the United States, advertisers spend more than $6 billion annually to advertise goods, services, and ideas in consumer

magazines. This amount accounts for five percent of the $125 billion total yearly outlay for advertising (McGann & Russell, 1988). Consumer magazines could well be one of the most dominant and popular national medium, to those who want to advertise their brands nationally.

Characteristics of Consumer Magazines

Magazines, which offer selectivity, excellent color reproduction, and a long issue life, are the only medium that regularly acquires repeat exposures. While consumer magazines are essentially a national medium, magazines are the most selective medium for reaching target audiences among national media.

The audience characteristics of magazines also create unique opportunities for advertisers, especially regarding selectivity. According to the Magazine Publishers Association (MPA), magazines cover 94 percent of all U.S. adults, who read an average of 9.9 different magazines each month (McGann & Russell, 1988).

While some national advertisers would enjoy this kind of coverage, there is a group of advertisers who look for a specific market segment. For them, magazines offer low circulation but specialized editorial matter along with the ability to divide the circulation into regional and/or demographic editions. These regional and demographic editions account for about 15 percent of all magazine advertising revenues (McGann & Russell, 1988).

While advertisements are one-dimensional, mostly restricted to a visual appeal, high color reproduction is a distinct advantage to advertisers. The necessity for fine color reproduction is obvious for certain kinds of product advertising such as food,

clothes, and cars. Further, through the use of unusual space units, interesting effects and high impact can be achieved.

Magazines have a long issue life. Readers keep magazines for long periods and often refer to them. This long issue life enables the advertiser to deliver his/her message long after the present campaign has formally ended. Magazines also have pass-along audiences that increase the reach.

While consumer magazines can give many excellent advantages to an advertiser, they have several shortcomings, too. Consumer magazines lack geographical flexibility compared to other media, possess a one-dimensional print medium, and fail to achieve broad reach due to their selectivity. Despite these weaknesses, consumer magazines could be a good choice in this research considering the fact that the present study assumes a typical brand which can be served well by magazines.

CHAPTER 4
THE COMPREHENSIVE MODEL
-- OPERATIONAL DEFINITION AND ANALYZATION

Introduction

This chapter turns to the development of a long-term optimization model to solve the stated media problem. For ease of presentation, this chapter is further subdivided into the following sections: (1) introduction, (2) sources of the magazine data, (3) constraints, (4) the objective function, (5) strategic elements of advertising media, (6) a procedure for obtaining the average gross rating points, and (7) a sample problem.

A microcomputer program that allows one to identify optimum advertising media plans has been developed to conduct the present research. Based on the framework proposed in Chapter 2, this microcomputer program will evaluate schedules based on the gross rating points (GRPs) which is the popular media objective. The GRPs in each schedule will be calculated from the estimation of the exposure distributions. In addition, the program will examine all the constraints and the strategic elements of advertising media except seasonality and geographical distribution. Rationales for eliminating those elements have been presented in the previous chapter. This program is capable of handling a single medium long-term media schedule and of generating an optimum schedule in that it will evaluate all the possible options. Figure 3 presents the overview of the comprehensive model used in this research, and the detailed explanations of each diagram in Figure 3 will be followed.

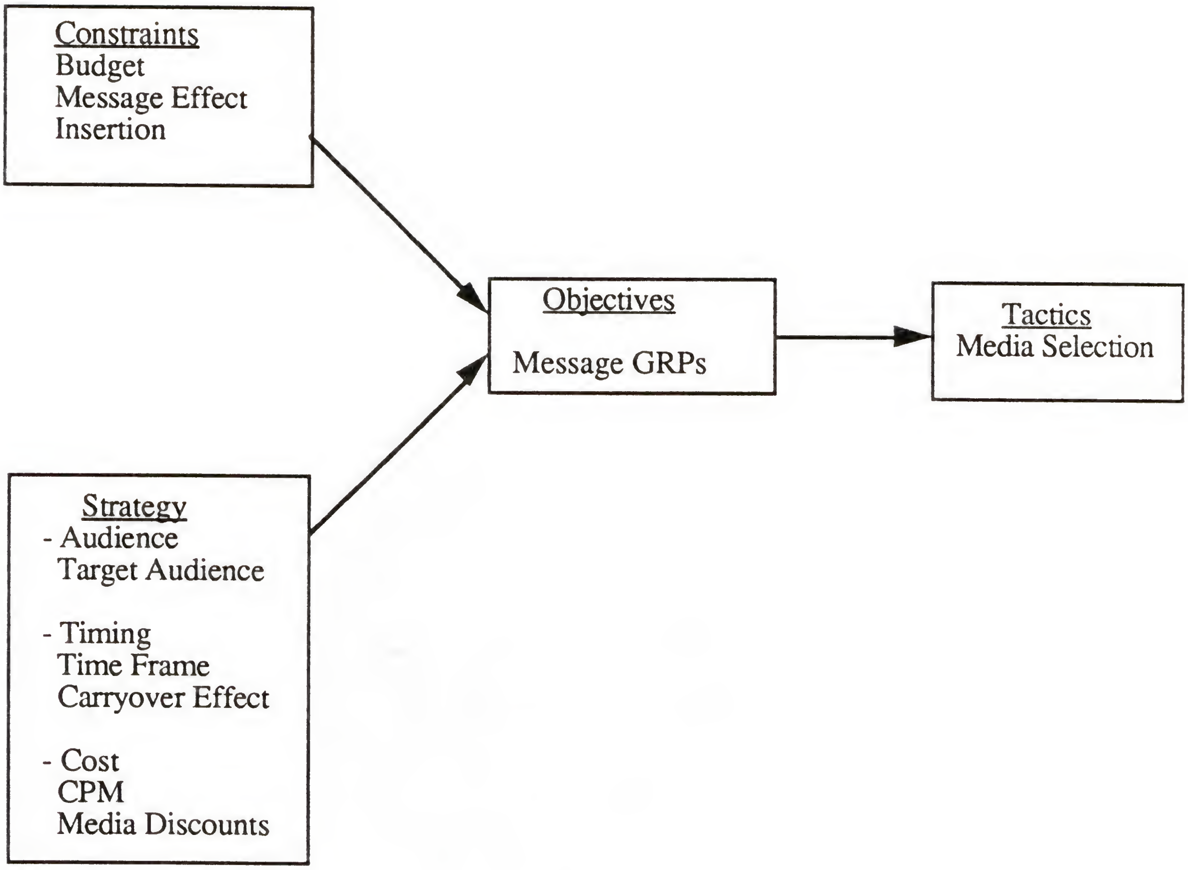

Figure 3. Overview of a Comprehensive Model for Single Media Long-term Optimization

The program, which is designed to evaluate the schedules for consumer magazines, demands that users build and store data bases for consumer magazines from which optimum schedules can be selected. These data bases contain vehicle names, costs per advertisement, target audience rating points, and maximum allowable monthly vehicle insertions. This same data base is used each month to form long-term data bases.

Sources of Magazine Data

The information necessary for the program data bases could easily be obtained by many major sources available to this medium in the U.S. First of all, the circulation figures and their rates are provided by independent auditing companies such as the Audit Bureau of Circulation (ABC), the Business Publications Audit of Circulations, Inc. (BPA), and the Verified Audit Circulation Corporation (VAC) which determine these figures by dividing the total number of copies distributed during the past year by the number of issues published. Standard Rate and Data Service (SRDS) then reports the findings from these companies. SRDS lists more than 1,500 consumer magazines and provides information such as editorial policy, advertising rates and discounts, mechanical requirements, copy regulations, circulation, personnel, and issuance and closing dates (Lancaster & Katz, 1988).

On the other hand, companies like Simmons Market Research Bureau (SMRB) and Mediamark Research Inc. (MRI) report the total exposure that includes primary and pass-along readership, which are detailed by such factors as demographic, geographic, socioeconomic, and media and product use. For the measurement of the vehicle ratings (R_i), SMRB uses a *through the book* survey method which "asks respondents to pick

magazines they have read in the previous six months after showing booklets which list about 110 magazine logos" (Lancaster & Katz, 1988, p. 7-1). Two-phase interviews are conducted to measure cross-pair audience ratings (R_{ij}), which represent the portion of the audience who read a pair of different magazines, and self-pair ratings ratings (R_{2i}), which represent the portion of the audience who read two issues of a magazine. On the other hand, MRI provides data that are similar to those provided by SMRB, which covers 250 magazines. Yet, MRI uses a survey technique called *recent reading*, which "asks the respondents if they have read any issue of a certain magazine in its most recent publication interval" (Lancaster & Katz, 1988, p. 7-3). Due to the differences in survey techniques, the estimation of audience readership between these two publications shows a slight difference.

As mentioned, the current model only requires only the information of vehicle ratings, duplications, vehicle costs, the size of the target audience, and vehicle discounts. This information can be obtained from the two sources, SRDS and SMRB. SRDS submits the information of vehicle costs and discounts, but SMRB provides data such as the size of the target audience, vehicle ratings, and duplications. MRI, an additional source available to users, gives data similar to those provided by SMRB.

Constraints

Optimization Constraints

Once the user has prepared a data base, the program will search for the best schedule, given the budget and insertion constraints and the average gross rating points (GRPs). The upper budget limit can also mean the size of the advertising budget,

which is the amount of the budget that an advertiser can afford. Since the goal of media selection is to find the best schedule given the amount of money that an advertiser could afford, this upper budget limit could be a natural constraint for optimization. In addition, the present model also sets another budget constraint, the lower budget limit. Ideally, the model should evaluate all the possible schedules with the schedule costs, ranging from one dollar to the upper budget limit, to guarantee the optimality of the schedule. This evaluation certainly requires a great amount of computation time. In addition, as the Media Group (1989, p. 3-4) notes, "It is unlikely that the cost of an optimum schedule will exactly meet the upper budget limit because differences in total schedule cost from one possible solution to another will be multiples of the typical vehicle cost. . . . It also speeds the search for a solution by eliminating schedules on the basis of cost alone without completing an extensive reach and frequency analysis for each of these options." Therefore, the author decided to accommodate the lower budget constraint into the program for the verification of the present model.

Message Factor

Creative factors such as emotional appeal, involvement, immediacy, message complexity, and the quality of the message are also important in media planning. These will influence not only the choice of media but also the model's ability to make accurate forecasts of advertising impact, despite the fact that these are non-media elements. Creative factors are considered strategic elements in media selection but categorized as constraints simply because these fall beyond the scope of media planning.

Since the syndicated data services publish ratings and duplication data in terms of the percentage of people exposed to the vehicles rather than to the advertisements,

the estimation of the scheduling impact based on this data, without having any adjustment mechanism, can end up with the vehicle estimation which is not of main interest to the advertiser. On the other hand, most magazine advertisements are audited and tested by commercial research companies such as Starch, Gallup & Robinson, or Burke, and the test results of this copy testing are available to most advertisers. This information can, then, be used to adjust the vehicle single-insertion ratings into the message ratings. Yet, there is no data available for the information on message self-pair (R_{2i}) and cross-pair (R_{ij}) duplications. Necessary for the appraisal of the exposure distributions, the self-pair and cross-pair duplications should somehow be estimated in order to calculate the message impact. There are at least three alternatives to evaluate message exposure distributions, and Figure 4 illustrates them.

The first method applies the same weights into the vehicle duplication ratings to get the message self-pair and cross-pair ratings. Once the message single and duplication data are obtained, these data are then inputted to estimate the message exposure distributions which are necessary to obtain the objective function values. Since all three ratings are available, the beta binomial distribution with a full information model should be used. It assumes that the proportion of the message ratings to the program ratings in single-insertions will be the same as that in duplication ratings.

The second method tries to estimate the message duplication after the single insertion vehicle ratings have been weighted to adjust the message factors. Message single insertion ratings are then inputted into the beta binomial distribution with limited information model. This model estimates the duplication and calculates the message exposure distributions using the weighted single insertion ratings and estimated

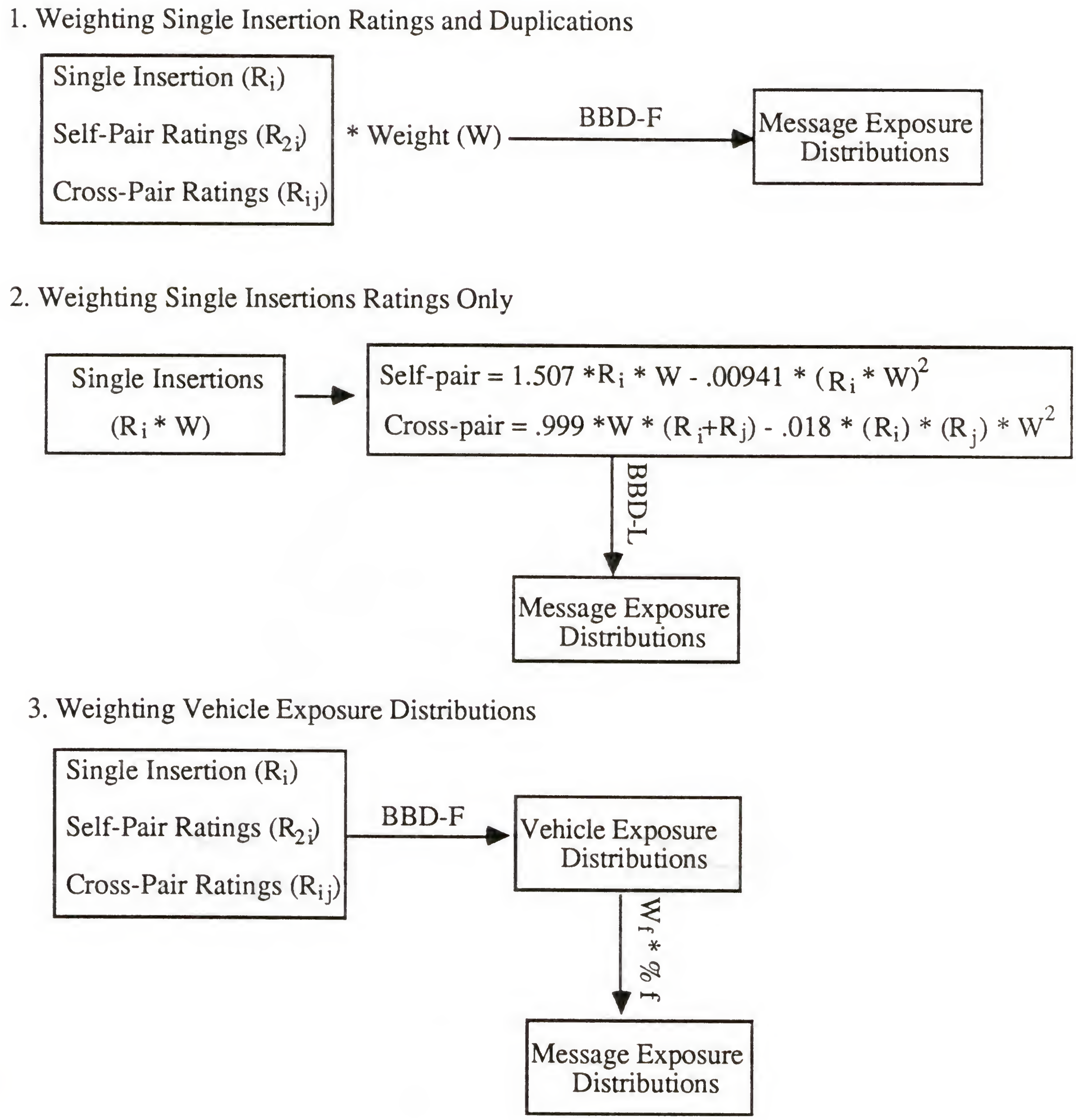

Figure 4. Weighting Procedures

Source: Lancaster, K. M., & Katz, H. E. (1988). Strategic Media Planning. National Textbook Company: Lincolnwood, Illinois, Chapter 3.

duplication data. This method assumes that the regression equations that are developed based on the vehicle ratings to estimate the duplication ratings will be applicable for the estimation of the message duplication ratings.

Instead of applying weights into the ratings, the third method applies the message weights into the estimated vehicle exposure distributions. Using the vehicle single and duplication data, the beta binomial distribution model estimates the vehicle exposure distributions. Next, various weights are applied in each frequency level considering that the percentage of the people who are exposed to the message after ten vehicle exposures will be much greater than that after one vehicle exposure. These weights might have a convex or S-shaped distribution, depending on the assumption planners make about consumer response to advertising repetition (Lancaster, 1989).

None of the above illustrated methods seems to be perfect. Yet, the third method may have more problems than the previous two, since these various weights tend to be very subjective. For instance, those who are exposed to the vehicle three times are not necessarily exposed to the message only three times. Among those, there are people who are not exposed to the message, some who are exposed to the message only once, or twice, and a very small portion of people who are exposed three times. To sort out these proportions at each frequency level and to apply various weights for them is very difficult.

The second method also poses some problems. This method estimates the self-pair and cross-pair ratings, which are supposed to hold the estimation error. In addition, when the message weights are applied to the vehicle ratings, the size of ratings will tend to be very small. Since the regression equations for the duplication ratings have been developed based on the vehicle ratings that are much higher than the

message ratings, the estimation of the duplication with very small ratings will cause more estimation error considering the nature of the regression analysis.

The first method also has a problem in that it has a-priori assumptions about duplication. However, this method is considered more reliable for several reasons. First, it applies the real vehicle duplication ratings. Secondly, the margin of errors caused by the application of the same weights on the duplication as that on the single-insertion ratings is considered to be much smaller than those caused by the other two methods. Therefore, the present model will adopt the first weighting procedure to examine the message effect.

Objective Function

Gross Rating Points

The computer model will select the optimal long-term solution based on the gross rating points (GRPs), which reflect the sum of the rating points of all insertions in the schedule. As the review of the literature suggests, it is desirable to evaluate the advertising media schedule in the form of media objectives such as reach (1+), effective reach (3+), average frequency, or gross rating points (GRPs). Due to the time consuming nature of these procedures, the present study will only incorporate one objective function among these. Optimization analysis with different objective functions may lead to a different recommendation of the schedule, but it is unlikely to reverse the significance of each element. The decision should then be made based on the appropriateness to the study and the superiority of the concept. Here, the findings from the Media Group study (1989) should be helpful. They indicate that optimizing

effective reach (3+), average frequency, or GRPs seem to lead to nearly identical solutions for consumer magazines while choosing reach (1+) generally leads to slightly higher levels of reach (1+), but substantially less favorable results for all other criteria. In addition, effective reach (3+) and GRPs are preferred to average frequency since their figures are produced upon consideration of message exposure distribution which reflects the quality of the schedule. On the other hand, effective reach (3+), by its definition, requires a minimum of three insertions to have any impact. Since the present study incorporates small scale data bases due to the size of the problem, the average gross rating points (GRPs) are selected to assign a value to a given media insertion schedule.

There are at least two ways of obtaining the value of gross rating points (GRPs). For a simple manner, GRPs can be estimated from the product of the vehicle ratings and their insertions. On the other hand, gross rating points (GRPs) can also be obtained through the estimation of the exposure distribution, and the formula for vehicle monthly gross rating points (GRPs) can be expressed as follows:

$$\textbf{GRPs} = \sum_{f=1}^{n}(f*\%f) \qquad (1)$$

where f = particular exposure number where $f = 0$ to N total insertions in the schedule
%f = percentage of the target exposed to each level of frequency

Source: Lancaster, K. M. (1989). ADLAB: For Advertising Media Planning on the IBM, Macintosh and Compatibles. William C. Brown Co.: Madison, WI.

Certainly, the former method is linear and much simpler than the latter. If the main interest in this study is to simply calculate the GRPs without considering any strategic elements, the values from both methods will be the same. Therefore, the former method will be preferred since it is much simpler than the other and there is no

reason to estimate with the exposure distributions. In this case, selecting GRPs as the objective function for the present analysis will not be desirable since this estimation will be linear. However, if the GRPs could be obtained only after having been adjusted by the various strategic elements where the different weights should be applied at the different level of frequency, the method of obtaining the GRPs from the product of the vehicle ratings and their insertions would no longer be valid. The estimation of the exposure distributions becomes an essential part of the algorithm, and the Equation 1 is the only way of obtaining the objective function of the present model. Finally, the message GRPs in the present analysis could become a non-linear and sophisticated mechanism in accessing the schedule impact.

The Beta Binomial Distribution with Full Information Model

As reviewed earlier, there are many ways to estimate the exposure distributions of a schedule (e.g., Danaher, 1989; Leckenby & Kishi, 1982b; Leckenby & Rice, 1985; Rust & Klompmaker, 1981; and Lancaster & Katz, 1988). These models are broken into two groups: univariate models, which only allow for a bimodal distribution, and multivariate models, which allow for a multimodal distribution. Among univariate models, some models do not require duplication, which makes the model simple and still acceptably accurate (Lancaster & Katz, 1988; Ju & Leckenby, 1989; Leckenby & Rice, 1985; and Headen et al., 1976). In this case, the duplication data are estimated either by the method of means and zeros (Leckenby & Rice, 1985), by the use of regression analysis (Lancaster & Katz, 1988; and Headen et al., 1976), or by the use of Poisson binomial distribution which does not require duplication data (Ju & Leckenby, 1989). While a more accurate estimation of exposure distribution may be

achieved with more complex models, a simple but reasonably accurate model is recommended in the application of the media selection model due to the complexities involved in the problem. Since comprehensiveness of the model is an important concern in the development of the media selection model, the accommodation of exposure distribution is essential. However, the parsimony of the model is also important since the model will not be practical without achieving it. Therefore, the estimation method, which is simple but reasonably accurate, will be the best choice here. For these reasons, univariate models are certainly preferred in the application of the media selection model.

Among many univariate models, the beta binomial distribution model has been chosen because the reliability of this model has been proven over decades (e.g., Ju et al., 1989; Kishi & Leckenby, 1981; and Leckenby & Boyd, 1984) and the use of the model has been heaviest in the advertising industry (Kreshel, Lancaster, & Toomey, 1985; and Leckenby & Kishi, 1982a). The beta binomial distribution model (BBD) is the composite model both of beta distribution which determines "the number of different ways that target members can be exposed to that schedule" (Katz, 1988) and of binomial distribution which determines "the probability of exposure to that schedule" (Katz, 1988). Considering the fact that the present model adopts the message weighting scheme which requires the actual vehicle self- and cross-pair ratings, <u>the beta binomial distribution with full information model (BBD-F) will be used for the estimation of the exposure distributions for this study</u>. The mathematical form of beta binomial distribution with full information model (BBD-F) is expressed as follows:

$$V_{f=0} = \prod_{f=0}^{N-1} (\beta+f)/(\alpha+\beta+f) \quad (2)$$

$$V_{f>0} = ({}_NC_f)(V_{f-1})(\alpha+f-1)/(\beta+N-f) \quad (3)$$

where: V = probability of exposure f times to the vehicles in a schedule

f = particular exposure number where $f = 0$ to N total insertions in the schedule

α = exposure parameter = $[\bar{R}_1(\bar{R}_2 - \bar{R}_1)]/[2\bar{R}_1 - \bar{R}_2 - (\bar{R}_1)^2]$

β = non-exposure parameter = $[A(1 - \bar{R}_1)]/\bar{R}_1$

N = total insertions in the schedule

$\bar{R}_1$ = average single insertion rating = $\sum_{i=1}^{m} n_i R_i / \sum_{i=1}^{m} n_i$

$\bar{R}_2$ = average pair-wise rating = $[(\sum_{i=1}^{m}(n_iC_2)R_{2i}) + (\sum_{i=1}^{m-1}\sum_{j=i+1}^{m} n_i n_j R_{ij})]/({}_NC_2)$

m = total number of vehicles in the schedule

n_i = number of insertions in vehicle i

R_i = audience rating of vehicle i (single-insertion or one-time rating)

R_{2i} = two-insertion rating of vehicle i (self-pair rating)

R_{ij} = rating of one insertion in each of vehicles i and j (cross-pair rating)

C = combination formula (e.g., in order of appearance, N total schedule insertions taken f at a time, n_i vehicle insertions taken two at a time, N total insertions taken two at a time)

Source: Lancaster, K. M. (1989). ADLAB: For Advertising Media Planning on the IBM, Macintosh and Compatibles. William C. Brown Co.: Madison, WI.

Strategic Elements of Advertising Media

Overview

As stated earlier, a strategy is a series of actions taken in order to accomplish specific and stated goals. In other words, media strategic elements are designed to

implement the overall media objectives. Since the goal of setting media strategies is to implement the media objectives, the estimation of the media objective without considering strategic elements certainly causes the validity problem of the model. In other words, when the media selection model estimates the impact of a specific schedule, the objective function representing the media objectives should somehow represent these specific elements to make the model comprehensive. Strategic elements considered in this model include time frame, carryover effect, media quantity discounts, cost efficiency, and target audience.

Timing of Advertising

The issues related to the subject of time frame include the unit of the time frame and the length of the planning period. In relation to the unit of the time frame, the empirical findings reviewed earlier predominantly support the monthly time frame. This unit did not have the data interval bias (Clarke, 1976) and is the most heavily used unit in practice (Lancaster et al., 1986). If the job of a model builder is to gather all the empirical findings and to accommodate the unit that is supported by them unless there are convincing reasons to stand against them, he/she should select the monthly time frame as the most appropriate unit in this issue. In addition, the author has decided to use consumer magazines to verify the model. Since the typical publication interval for consumer magazines is a month, the unit of the time frame which is shorter than a month would not be appropriate here. Therefore, the present model will accommodate a month as the basic time unit of the model.

One other issue related to the subject of time frame is the length of the time frame. Considering the fact that the length of typical media planning in practice does not exceed to a year, a model needs the ability to recommend a yearly schedule so that it

has more flexibility to accommodate any length of the schedule. However, this would require huge options to evaluate. The optimization analysis, even with a small data base, would become very difficult to conduct. Generally speaking, the size of the problem can be determined by the size of data base and the length of the time frame. A longer time frame often requires evaluation of a smaller data base. Yet, a shorter time frame would prevent the model from examining the effects of the timing of advertising. After considering both sides of the problem, the author has decided to adopt the six month planning period for the verification of the model.

Carryover Effect

From the review of the past literature on the carryover effect on cognitive criteria, the empirical findings support that the rate of carryover geometrically decreases as time progresses (e.g., Ebbinghaus, 1885; Postman & Rau, 1957; Greenberg & Garfinkel, 1962; and Craig et al., 1976). However, these studies have failed to suggest any type of the regression equations between the two concepts since most of these studies have adopted the experimental design which does not produce enough data to do that. On the other hand, studies from the economic discipline have also examined the effects of carryover (e.g., Aaker et al., 1982; Rao & Miller, 1975; Bass & Clarke, 1972; and Weiss & Windal, 1980). Although these studies have focused on the carryover effect on advertising rather than on exposure, the results of these studies have also showed the negatively accelerated carryover curve. In addition, these studies have suggested various forms of the regression equations. Since the author believes that the shapes of the equation are not situation-specific, the regression equation developed from this domain would also be useful in explaining the carryover effect on exposure. The studies from both subjects have suggested the same negatively

accelerated carryover curve. Among the various types of carryover equations, the present model has adopted the geometric lag function of the carryover effect since this is the most commonly-used lag model in this domain (Clarke, 1976). This formula represents the geometric lag model:

$$Y_t = X_t + \lambda X_{t-1} + \lambda^2 X_{t-2} + \lambda^3 X_{t-3} + \lambda^4 X_{t-4} + \ldots\ldots + \varepsilon_t \qquad (4)$$

where: Y_t = Total amount of exposure in *t* th time period after cumulating the amount of carryover from the previous time periods

X_t = Amount of exposure produced from the schedule in *t* th time period alone.

λ = Carryover rate

However, the findings from past studies also show that the effect of the carryover only lasts three to four time periods (Clarke, 1976). If the effects of the carryover do not exist after a certain time period, examining the effects that do not exist is plausible. In addition, counting all the carryover effect in past time periods would increase the complexity of the problem. Considering the fact that the optimization problem is such a complex task and the parsimony of the model is an important concern to model builders, the author omits the effects that do not seem to exist and that are not likely to affect the impact of the schedule. Through the examination of the lag structure as well as the past findings, the present study adopts carryover effect on the past three time periods. Then, Equation 4 reduces to this formula:

$$Y_t = X_t + \lambda X_{t-1} + \lambda^2 X_{t-2} + \lambda^3 X_{t-3} \qquad (5)$$

Once, the structure and the duration of the carryover effect has been decided, the next concern of this subject is the size of the carryover effect. How much of the

exposure in the previous time periods will be carried over to the present time period? Concerning the size of the carryover rate, the review of the literature has concluded that the amount of the exposure carried over will vary depending on the factors such as meaningfulness of the stimuli, similarity of items, the size of the advertising message, and the level of original learning itself (e.g., Laband, 1989; Underwood & Schultz, 1967; Strong, 1914; and Underwood, 1964). In other words, these findings seem to support the fact that the size of the carryover will be mainly determined by the creative effort put on the specific campaign. Therefore, the present model will allow the user to input the amount of initial carryover.

On the other hand, the review of literature has also revealed that both the amount of the exposure given in a specific time period, which will vary by the size of the exposures themselves, and the various creative factors affect the size of the carryover rates (e.g., Rethans et al., 1986; Calder & Sternthal, 1980; and McCullough & Ostrom, 1974). These advertising repetition effects draw a special attention here since the present model adopts the exposure distributions of the advertising frequency. The advertising repetition effects could mean that a group of people who have been exposed to the message more will have a higher chance of remembering that message in the subsequent period. In other words, once the initial carryover rate has been determined by the various creative factors, the different rates of carryover should be applied according to the different levels of advertising frequency within a specific time period. As reviewed earlier, the studies on the advertising repetition effects on exposures predominantly reported the convex curve depicting perceptions of diminishing returns to advertising frequency (e.g., Appel, 1971, Grass & Wallace, 1969, Ray & Sawyer, 1971, Strong, 1916, Obermiller, 1985, and Hitchon et al., 1988). In addition, a majority of media planners in practice also believe that the curve

should be convex (Lancaster, Pelati, & Cho, 1991). Therefore, the author has decided to adopt the convex curve to examine the advertising repetition effects on advertising carryover.

However, studies on the advertising repetition effects on exposure have failed to suggest any type of regression equations of this convex curve since the results from these studies have been brought through the analysis of the experimental approach. This approach typically measures, the amount of recall or exposure in a few time periods such that it could not produce enough data to conduct the regression analysis. On the other hand, Lancaster et al. (1991) conducted a survey on the perceptions of leading media directors about advertising repetition effects. They asked the directors to draw the repetition curve and gathered a total of 73 curves. Although the perceptions of media directors about advertising repetition effects are not exactly the same as the advertising repetition effects, these perceptions could be a good instrumental variable since no such data are available at the present time. In addition, since the main focus of this regression analysis is to discover the slope of the curve rather than to find an intercept and the slope where the initial carryover rate could be determined by various creative factors, a great amount of difference between the perception and the real exposure is not expected. The decision adopting such a curve is substantially more significant than the decision regarding the slope of the curve. Therefore, these perception data are used to get the slope of the regression equation.

Among the various types of convex curves, the present study has adopted the modified exponential function simply because it has a built-in upper limit. This is an essential property for the present analysis since the amount of the carryover cannot exceed 100 percent. Other convex functions, which do not have the upper limit, could easily go beyond this limit in a case where the initial carryover rate is close to 100

percent. The original form of the modified exponential function is expressed as the following formula:

$$\lambda_f = \bar{\lambda}(1 - e^{-b*f}) \tag{6}$$

where: λ_f = Amount of the advertising carryover at frequency *f*

$\bar{\lambda}$ = The upper carryover limit. In this case, $\bar{\lambda} = 1$

f = Advertising frequency

Source: Leckenby, J. D., & Wedding, N. (1982). Advertising Management: Criteria, Analysis and Decision Making. Grid Publishing, Inc.: Columbus, Ohio.

One other concern about the effects of repetition on advertising carryover is the initial carryover rate, which will be determined by other creative efforts and will be given so that the equation should represent the initial carryover rate when the frequency is equal to one. To do so, Equation 6 has been slightly modified into the following equation:

$$\lambda_{f=} \bar{\lambda}(1-(1-\lambda_1) * e^{-b(f-1)}) \tag{7}$$

The regression analysis has been conducted to get the parameter in Equation 7 using the perception data obtained from the study conducted by Lancaster et al. (1991). Finally, the probability of the advertising exposure with variable carryover effect could be estimated in the present model using this equation. The final form of the equation on the advertising carryover effect used in this study is stated as follows:

$$P^*_{t,f>0} = P_{t,f} + (P_{t-1,f})[\bar{\lambda}(1-(1-\lambda_1) * e^{-b(f-1)})] + (P_{t-2,f})[\bar{\lambda}(1-(1-\lambda_1) * e^{-b(f-1)})]^2$$

$$+ (P_{t-3,f})[\ \bar{\lambda}(1-(1-\lambda_1) * e^{-b(f-1)})]^3 \qquad (8)$$

$$P^*_{t,f=0} = 1-\ (\sum_{f=1}^{N} P_{t,f}) \qquad (9)$$

where: V = probability of exposure *f* times to the vehicles in a schedule

f = particular exposure number where *f* = *0* to *N* total insertions in the schedule

t = particular time period where t stands for the present month

N = total insertions in the schedule

P = probability of exposure *f* times to advertising messages in the schedule

P* = Probability of exposure with carryover effect

λ = carry-over rate of audience exposure to an advertising message given a **single** vehicle exposure.

b = empirically derived perimeter to increase λ with *f* to account for increased probability of advertising message exposure given **multiple** vehicle exposures. In this model, b = .087 (N=73, R^2=.56).

In evaluating a long-term plan, the beginning and end of the planning period require special consideration. At the beginning, starting exposure levels must be specified unless a brand is completely new. At the end, a way to evaluate advertising insertions whose effects extend beyond the planning period must be found. The present model incorporates both of these concerns. For the end of the planning period, the model could handle this problem simply by adding a few extra periods without scheduling more insertions and by calculating the overall objective value. At the beginning, a user can simply input starting exposure levels based on the amount of advertising in the last few periods of the previous year's media schedule.

Media Quantity Discounts

The literature review in Chapter 2 showed that the nature of the media quantity discounts could affect the value of the media and its vehicles (Kaplan & Shocker, 1971). Many authors of media planning texts have also expressed a serious concerns about the importance of these effects (e.g., Scissors & Surmanek,1982; and Jugenheimer & Turk, 1980). Yet, the review has also shown that very few media selection models have tried to accommodate these elements into their model due to the complexity of the cost structure.

While an advertiser can achieve extra savings with volume purchase, the effect of quantity discounts could give a model builder serious problems. Quantity discounts in media selection mean unfixed vehicle costs, all of which depend on the number of vehicles a schedule purchases. In other words, when one wants to evaluate all possible options in the data base, he/she should input different rates of vehicle costs in each schedule. To make matters worse, every media vehicle offers different rates of media discount so that incorporating them into a model is very difficult. Yet, this effect can usually make the purchase of additional insertions possible which will affect the overall impact of a schedule. Since the present study focuses on long-term planning, where volume purchase can be typical, this effect is hard to neglect.

Along with carryover effect, this effect is considered to be the major time consuming routine in the selection of media. Thus, it is quite understandable that few model builders have designed their models to consider media quantity discounts. Neither developing functional relationship between the frequency of purchase and discount rates nor inputting all the different rate of vehicle discounts seems to be desirable. The intention of the present study is not to develop a systematic way of incorporating these effects into a model, but to allow the models to take into account

this effect in the optimization of the long-term schedule. Since the present study analyzes only a very small number of vehicles, inputting them into the model is not, in fact, hard. Thus, the present model will develop a data base which will contain the discount rates of every vehicle used in the optimization analysis.

Cost Efficiency

As shown in Chapter 2, cost efficiency plays an important role in formulating the data base to be optimized. The cost efficiency is typically calculated by dividing the costs by the product of target size and ratings. By scrutinizing the value of each vehicle, a planner may or may not select a vehicle for his/her brand's advertising. The present model will also follow the above mentioned procedure. In the formulation of a data base, cost efficiency will play a significant role in the selection of vehicles. In addition, cost efficiency can also give a planner useful information in evaluating a schedule. Although the optimal schedule should be produced through the examination of objective function, a schedule with better cost efficiency will be selected over the other if the objective function value among schedules is the same. The model will also be able to produce these figures once the optimal schedule has been produced (Figure 3, p. 63).

Target Audience

For efficient advertising, advertisers usually define a target group of consumers as the most likely prospects for purchasing their products and try to satisfy the wants and needs of their specific target audience. As reviewed earlier, the target audience also

plays an important role in the data base formulation stage. By inputting all the ratings in terms of the target audience, the estimation of the schedule impact is calculated in terms of the target audience rather than of the general public (e.g., Lancaster, 1988 and 1987; and The Media Group, 1989). To select those vehicles, one should first know the proportion of the target audience who watched a specific vehicle, not the proportion of typical adults. Syndicated services such as SMRB or MRI publish those figures. Thus, ratings for the target audience will be inputted for the optimization of the schedule.

On the other hand, the size of the target audience can be used to calculate some important media planning concepts such as cost-per-thousand impressions (CPM) and gross impressions. The present model will be able to produce these figures once optimal schedules have been produced. Although this factor is not actually involved in the calculation process of estimating message GRPs, the accommodation of this factor into the model is, therefore, important.

Procedure for Obtaining the Gross Rating Points

As Figure 5 briefly presents, the model cannot generate the long-term gross rating points with a single step procedure. In the data base formulation stage, vehicles based on the cost efficiency figures and the ratings of vehicles are inputted in terms of target audience. Message weights could now be applied in order that all the figures produced from the model can be considered the message effect rather than the vehicle effect . While vehicle rating refers to the portion of the target exposed to the vehicles, message rating refers to the proportion of the target exposed to the advertisements. Once the user orders the program to generate the optimal schedule after

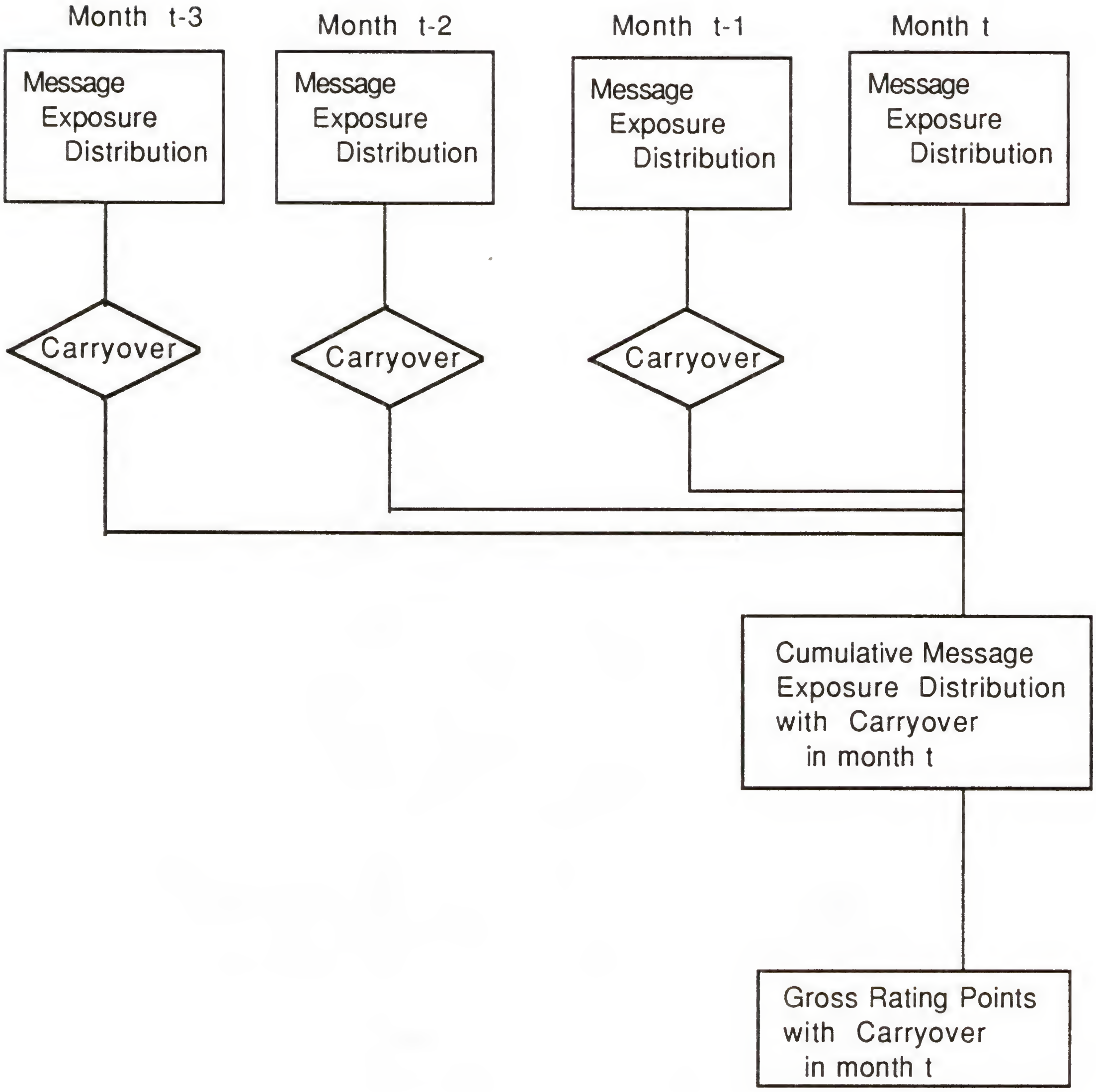

Figure 5. Procedure for Obtaining Monthly GRPs with Carryover Effect

inputting required information such as the lower and upper budget limit and target size, the model starts to evaluate schedules based on the scheduling costs. In each option, the model calculates the long-term advertising cost. Based on the number of insertions to be used in each vehicle within the planning period, appropriate media quantity discounts are applied to adjust the actual vehicle cost. The sum of the product of each vehicle insertion and cost will constitute total advertising cost. If the cost of an option does not meet the budget constraints, the program eliminates the option from further consideration.

Once the option meets budget constraints, the model evaluates *GRPs with carryover effect* for each month. The model estimates message exposure distributions for the present month and those for the past three months with carryover weights. The various rates of carryover weights are applied to different levels of exposure distributions. To estimate the message exposure distributions, the present study uses the popular beta binomial exposure distribution model. These distributions are then combined together to form a single message exposure distribution with carryover effect within a certain month[1].

A sum of the portion of the target exposed to each level of frequency and the corresponding frequency will be the gross rating points (GRPs) for that month. The

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[1] Combined Message Exposure Distribution

$$CV_f = \sum_{k=0}^{f} \prod_{k=0}^{f} (M_{i,k})(M_{j,f-k})$$

where *V*, *M*, and *f* are as defined above, and where:

C = Combined exposure distribution based on a pair of separate message exposure distributions *i* and *j*.

Source: Lancaster, K. M. (1989). ADLAB: For Advertising Media Planning on the IBM, Macintosh and Compatibles. William C. Brown Co.: Madison, WI.

sum of each month's gross rating points (GRPs) can finally be the objective function for a given media insertion schedule.

Sample Problem

To better understand the nature of the present model, the present section illustrates a sample hypothetical problem. A media planner in brand X is going to develop a four-month media plan using the present model. The target market for brand X is typical adults (age 18+). According to *ADWEEK's Marketer's Guide to Media* (1988), the target audience size is 176,200,000. Through situational analysis, the planner has decided to advertise only in consumer magazines and has selected two magazines that seem the most appropriate for his brand. Table 3 presents the two magazines selected for this campaign, and their ratings in terms of the target audience, costs, and maximum number of insertions. The four month advertising budget for brand X is $750,000.

Table 3
Consumer Magazine Monthly Data base

Magazine	Rating	Ad Cost	Maximum Insertions
1. *TV Guide*	24.5	$104,600	2
2. *Reader's Digest*	21.5	115,300	1

Source: *ADWEEK's Marketer's Guide to Media*, New York: A/S/M Communications Inc., Fourth Quarter, October-December, 1988.

For the optimization analysis, the model asks the user to input data such as the size of the target audience, vehicle single-insertion and duplication ratings, vehicle costs and their discounts, and the maximum number of insertions. Once the planner has entered the necessary data, the model, then, requests the upper and lower advertising budget limits. The advertising budget for brand X should always be a upper budget limit. The planner should give an ample gap between the upper and lower budget limits unless a solution may not be feasible. Here, a lower budget constraint of $500,000 is used with an upper budget limit of $750,000.

As soon as the planner inputs the budget limits, the program starts to optimize. At first, the program evaluates all the possible options within a single month (In this case, the total number of the options in a month would be 3*2=6), then saves the exposure distributions of all the options, their corresponding vehicle names, and insertions. Once the model has completed the single month optimization phase, it then proceeds into the long-term optimization routine. Here, the program randomly mixes every single month's options through the four-month period. In each option, the program first estimates the schedule cost after applying the proper discounts. If the option does not meet the budget constraints, the model goes to the next option. If the option meets the budget constraints, the model estimates the objective function value using the exposure distributions. After the value of the objective function has been obtained, the model then compares the size of this value to that of the best value obtained from the previous schedule. If the obtained value is higher, the model saves the value and the schedule. If not, the model proceeds to the next option. The searching routine continues until all the possible options have been evaluated.

Although the program does not report much information during the run, it reports the total schedules evaluated at the time of the report to assure that the program

is functioning properly in view of the large number of schedules typically evaluated. Figure 6 displays the solution the computer program offers for this problem after considering 1,296 possible schedules. It also shows that the highest possible average monthly GRPs is 41.8, given the planning constraints. The optimum solution recommends more purchase of *TV Guide* and no advertising in the second month, which indicates the pulsing schedule. The schedule cost at $705,244 is in fact close to the upper budget limit of $750,000.

Upper Budget Limit : $ 750,000

Lower Budget Limit: $ 500,000

Average Monthly GRPs: 41.8

	Past Advertising t-2	Past Advertising t-1	Month 1	Month 2	Month 3	Month 4
TV Guide	2	2	2	0	2	2
Readers Digest	0	0	1	0	0	0

Total Cost : $ 705,244

Computation Time: 1 minute 50 seconds.

Figure 6. Sample Long-term Optimum Solution

CHAPTER 5
THE METHOD

Overview

A major motive for this study is to find a way of developing better and more reliable media selection models. The author believes that the past media selection models have been unreliable and not comprehensive. This dissatisfaction with the past models occurs because there is little information on the nature of the media selection process. It is neither certain what media variables are involved in this process nor how each variable affects the selection of vehicles. To make matters worse, there seems to be no consensus about which objective function a model should use in selecting an optimum schedule. The author doubts whether most model builders have a global picture of the media selection process which is essential in developing a better model. To have this picture would require model builders to understand the whole media planning framework and to understand the role of each variable in the framework.

So far, the present study has proposed the ideal media selection framework based on the review of major media planning publications (Figure 2, p. 26). Following this framework, this study has evaluated media selection models in the past (Table 2, pp. 31-32) and found a need to develop more comprehensive media selection models. Within the scope of single media optimization, the present study has developed a more comprehensive media selection model reflecting the ideal media selection model proposed in Figure 3 (p. 63).

Even though the conceptual importance of each element in the model is now quite understandable, how each element in the model fulfills its part in determining an optimum schedule among many schedule alternatives is unknown. In this section, the current study will validate each element of the proposed model. This model validation will allow us to assess how significant each element is in the estimation of the objective function and in the selection process of the optimal schedule. By examining the impact of each element in the model, the results from the present study will show the importance of embracing each element and help identify some elements which are important but do not affect the outcome of the solution to achieve parsimony of the model.

At this moment, some readers may wonder why testing each element in the media selection process is necessary. The inclusion of any element in the model means an additional estimation mechanism which may lead to a different solution. However, the author has reason to challenge this argument. For example, the examination of media quantity discounts in the model will lower the schedule cost in each schedule, but such savings may not be good enough to include additional purchase of any vehicle if the savings amount to only several thousand dollars. Then, vehicle selections in the optimum solutions will not, change despite the fact that the total schedule cost for that schedule has been lowered. In some cases, such as the application of the message or carryover weights, an additional mechanism would lead to a different value of the objective function (i.e., GRPs), but would not necessarily change the vehicle selections which is the main subject in this verification stage. If the examination of an element in the model will only affect the size of the objective function without changing vehicle selection of the optimum schedule, there may be no need to examine such an element in the optimization stage where all the options are compared. Instead, after the model

selects the maximum GRP producing schedule without examining that element, the correct GRP value can be re-estimated to save the computation time. Therefore, in a situation where the main focus in this verification is whether an element will affect the vehicle selection, there is no guarantee that an examination of an element will lead to a different vehicle selection. This verification process tries to resolve this problem.

Among the elements in the proposed model, cost efficiency and target audience are not appropriate to verify since they will only be considered in the data input stage. Since media planners in practice are already selecting the vehicles that are cost efficient in terms of their target audience, there is no value for this study to state that media planners should select the more cost-efficient vehicles in terms of their target audience. Therefore, only elements that are involved in the main estimation of the model will be tested for their significance in the model. These elements include time frame, carryover effect, message effect, and quantity discounts. The size of the advertising budget affects both the selection of vehicles and the quantity of the advertising, which has a relationship to media quantity discounts and other elements. Therefore, the advertising budget is treated as a constraint variable.

Research Design

Research Framework and Sampling Procedure

As shown in Chapter 3, the present study will test the impact of three strategic elements and the impact of two constraint elements on the media selection process. Strategic elements in the proposed media selection model include timing of advertising, media quantity discounts, and carryover effect. And, the constraint element in this

model includes advertising budget and message effect. For each element, two types of treatments, one for including an element in the model and the other for excluding an element from the model, have been devised to test the impact of each element. In addition, for carryover and message effect, where the size of the elements has been determined to vary depending on the situation, the two different levels of carryover and message effect (i.e., high and low) will be tested. Therefore, the verification process of the elements in the present model requires the Timing of Advertising (2) * Budget (2) * Message Effect (3) * Media Quantity Discounts (2) * Carryover effect (3) design.

As Figure 7 illustrates, this two (i.e., advertising budget) by two (i.e., timing of advertising) by three (i.e., message effect) by two (i.e., media quantity discounts) by three (i.e., carryover effect) design contains a total of 72 cells, or a total of 72 different treatment groups. To illustrate, only the optimization analyses within a cell receive the same treatments (e.g., the degree of the message weight or the use of media discounts). Therefore, this study requires a minimum of 72 optimization analyses to get any result. Care must be taken since half of the optimization analyses in this study must be done under the framework of aggregate monthly optimization analyses which is the duplicated sum of a monthly optimization schedule (Figure 7). Although these results are important to test the timing of advertising variable, they may not be quite useful in testing other elements such as carryover effect, media quantity discounts, or message effect. For these variables, the current study attempts to know the impact of each variable on the selection of long-term optimization schedule where vehicles are alternated to select the largest GRPs producing schedule. Therefore, the results obtained through long-term optimization analyses will only be used to test these variables, other than the timing of advertising variable.

Sampling Frame (N=720)			BUDGET LEVEL											
			Low						High					
			MEDIA DISCOUNTS						MEDIA DISCOUNTS					
			No Discounts			Discounts			No Discounts			Discounts		
			CARRYOVER EFFECT			CARRYOVER EFFECT			CARRYOVER EFFECT			CARRYOVER EFFECT		
			No	Low	High	No	Low	High	No	Low	High	No	Low	High
Timing of Advertising (Considered)	Message Effect	No	10	10	10	10	10	10	10	10	10	10	10	10
		Low	10	10	10	10	10	10	10	10	10	10	10	10
		High	10	10	10	10	10	10	10	10	10	10	10	10
Timing of Advertising (Ignored)	Message Effect	No	10	10	10	10	10	10	10	10	10	10	10	10
		Low	10	10	10	10	10	10	10	10	10	10	10	10
		High	10	10	10	10	10	10	10	10	10	10	10	10

Figure 7. The Research Design for the Verification of the Proposed Media Selection Model

As will be later explained in this chapter in more detail, the present research will select pairs of magazines from the top 30 rated magazines in both male and female target audience groups. Since each magazine has a different cost structure and ratings, it is impossible to generalize the findings from the optimization analyses of the various treatments with a single pair of magazines. On the other hand, if we conduct this verification analyses with all the possible pairs of magazines, there will be no need to worry about the sampling procedure. However, the number of the optimization analyses will be too large to handle (i.e., ${}_{30}C_2 * 72 * 2 = 62640$). Since the main concern of this verification analysis is to see if the results will hold in any combination of the magazine costs and ratings, the only way to solve this problem is to sample and to predict using the statistical method.

Then, the decision of the size of the sample becomes important. Although increasing the sample size certainly increases the accuracy of the results, this increase will result in more time and effort. Yet, care must be taken in deciding the size of the sample since a sample that is too small will jeopardize the accuracy of the result. In addition, it is not always desirable to have a larger sample. The law of diminishing returns certainly affects the sampling accuracy. In other words, a large increase of the sample size may only reduce the sample error by a small percentage. Then, the question is how to determine the optimal sample size.

To decide the size of the sample, three factors must be considered: the heterogeneity of the population, the magnitude of acceptable error, and the confidence level (Zikmund, 1982). The formula for calculating the sampling error can be stated as follows:

$$E = Z\frac{S}{\sqrt{n}}$$

where:	E =	Acceptable magnitude of error
	Z =	Standardization value indicating confidence interval
	S =	Sample standard deviation
	n =	Sample size

To estimate the standard deviation of the population, a pilot study which analyzed 72 solutions was made. The estimated standard deviation of Adjusted GRPs was 62.85. Considering the fact that most advertising research accepts the confidence interval at the .15 level of which standardization value is 1.44, the author thinks that a sample size of 720 analyses will be appropriate for the present analysis. This will give a margin of sampling error of $\pm$ 3.5%. At this level, if the study increased the sample size to 1,440, this increase could only reduce the margin of error by one percent. Considering the time and effort that the author can devote to this study, the author thinks this size is the optimal level for this study.

Independent Variables

Background

The present study will test every element in the media selection model that is involved in the media impact estimation process. Throughout this dissertation, the author has determined that there are four important elements that may have significant influence in the media selection process in the model. These elements include carryover effect, the use of media quantity discounts, timing of advertising, and message effect. For message and carryover effects whose sizes of the initial weight can be situation specific, two different sizes of the weights are tested to see if the size of the weight can be a factor in selecting the schedule that produces the largest GRPs (i.e., optimum

schedule). These four elements in the model will be the major independent variables tested in this study. Another variable such as advertising budget, which may have indirect effect on the objective function, will be treated as a constraint variable.

Carryover effect

Three different levels of this variable will be used for the present analysis: no carryover effect, low carryover effect, and high carryover effect. Certainly, to test the impact of the carryover effect, a comparison of the difference in the value of the dependent variable between the model that has a carryover function and the model that does not is necessary. In addition, the findings of the past studies on this subject have revealed that the rate of carryover on advertising exposures should vary depending on the quality of the creative campaign. Therefore, two different levels of the carryover rates have been included to test how this difference affects the value of the dependent variables.

Concerning the value of the carryover rates, Clarke (1976) found from the survey of the 69 econometric studies that the average value of the advertising carryover effect on sales in the monthly time frame was .44. Although this is not the value of the carryover effect on advertising exposures, the value which should vary depending on the creative effort is expected not to deviate significantly from this value. Thus, the author in the present study has decided to use .35 for the low carryover group and .55 for the high carryover group.

Media quantity discounts

To test the impact of the media quantity discounts, two treatments will be applied: one group with solutions from a model that examines media quantity discounts

in estimating a schedule cost and the other with solutions from a model that ignores media quantity discounts.

Timing of advertising

Two different levels of this variable will be used for the present analysis: a group of solutions from a model that not only evaluates the schedule alternatives with different combinations of advertising across months but also evaluates the schedule alternatives with same advertising across months (i.e. long-term optimization analysis) and a group of solutions from a model that only evaluates the schedules alternatives with same advertising across months (i.e. aggregate single month optimization analysis).

Message effect

The verification of the message impact requires three treatments: no message weights, low message weights, and high message weights. Concerning the size of the message weights, Lancaster et al. (1986) found that the average message weight that media directors used in consumer magazines was .525. Although the size of the message weights should vary depending on many factors such as the size of the ad, the use of color, or the location of the ad, it should not deviate much from this value. Therefore, in this study, the determination of the size of the weights for low and high groups will be based on this value. The present study will use .4 for the low message weights group and .6 for the high message group.

Advertising budget

This variable is considered the constraint variable. A higher budget will allow the model to suggest the optimum schedule with larger message GRPs and with more selection of the vehicles. Yet, different budget levels may affect the outcome of other independent variables. Therefore, the control of this variable becomes necessary.

Concerning the size of the budget between the two groups, the present study will determine the two levels of the advertising budget based on the fixed percentage of the total data base cost rather than by applying the absolute amount. SRDS shows that the costs of consumer magazine advertising vary from less than $10,000 to more than $100,000. If two low cost magazines are selected, $100,000 could be considered a high budget level. By contrast, in a situation where two high cost magazines are selected, this amount could be considered a low budget level. Therefore, the fixed amount of an advertising budget could lead to an inconsistent analysis. Therefore, the present study will use 40 percent of the total data base costs for the low budget level and 60 percent of it for the high budget level.

In addition, the lower budget limit has been set to speed up the analysis. As explained in Chapter 4, a narrower gap would make the analysis faster, but there is a danger of missing an optimum solution. Certainly, the wider budget window would demand an excessive amount of computation time. The author decided that the lower budget level will be set at 80 percent of the upper budget level. This budget window will force the model to evaluate approximately 11,000 schedules out of a total of 46,656 options. Considering that a great number of options will exceed the upper budget limit and will be far below the advertising budget, the author thinks a fourth of all possible options will give an ample room to find the best solution.

Dependent Variables

The independent variables in this study can be tested in two ways: in the value of the objective function and in the selection of the vehicles. The test of an impact of an independent variable on the selection of vehicles and their insertions will try to reveal if the media selection model that incorporates a certain element indeed suggests a different media selection schedule from the one that the model without that element suggests in terms of the selection of vehicles and their insertions. The test of an impact of an independent variable on the objective function (i.e., gross rating points) will verify if such a difference in the selection of the vehicles will lead to different estimated gross rating points (GRPs) between the two schedules.

Yet, it is very important to note that the verification of an impact on the objective function cannot be achieved simply by comparing GRPs estimated from the optimization model. The main agenda in the test of the impact on the objective function is to determine how much gross rating points (GRPs), the difference in vehicle selections between two solutions, could be responsible for. If there is no reason to doubt that the difference in gross rating points (GRPs) suggested from the optimization model between the two solutions (i.e., one from a model that incorporates an element and the other from a model that does not) should be equal to the amount of GRPs responsible for the difference in vehicle selections between the two solutions, then a simple comparison between these two gross rating points (GRPs) will verify an impact on the objective function.

But, the author has reason to discourage this comparison of GRPs suggested from the model in this verification process. The present study applies three different sizes of carryover and message weights (i.e., high, low, and no weights) in verifying the model. These differences in the size of weights not only should affect the vehicle

selection of the schedules that produces the largest GRPs (i.e., optimum solutions) but also should affect the size of GRPs of those optimum solutions. Yet, these variable weights, themselves, will also affect the value of GRPs. Then, the amount of difference in GRPs of the optimum solution represents the mixed product of the variable weights effect and the effect of the difference in the selection of the vehicles between the two solutions (i.e., one from a model that incorporates an element and the other from a model that does not).

To neutralize the effect of the variable carryover and message weights on the estimation of GRPs, the author applies the constant message and carryover weight and re-estimates GRPs for the optimum solution suggested from the original model. In other words, to see how each element in the model will affect the media selection process, the present study first applies the variable weights in the optimization analysis. Once the model recommends the optimum solution, this study re-estimates gross rating points (GRPs) with constant message and carryover weights for the optimum solution. The re-estimated GRPs will be used to test the impact on the objective function and the difference in this value should reflect the effect of the difference in media selections. From now on this value will be called adjusted gross rating points (AGRPs). In this study, the mean of high and low message weights and that of high and low carryover weights were used for the constant weight (i.e., .5 for constant message weight and .45 for constant carryover weight).

Although simple GRPs are a more realistic value in the estimation of media impact, they are no longer the main focus in testing the impact on the objective function. These simple GRPs are not necessarily useless in this study. First of all, the schedule that produces the largest GRPs is selected based on the value of simple GRPs

in the optimization analysis. Second, even though the difference in GRPs does not justify the examination of an element in the optimization analysis as explained above, it can be a justification for the use of an element in the estimation of reliable media impact. In other words, if an element in the model makes a significant difference in GRPs of the optimum schedule but does not make a difference in vehicle selections, the model does not have to examine this element in the optimization process but has to re-estimate the media impact in order to estimate a correct media impact after the optimization analysis is done. Therefore, although the AGRPs will be used for hypotheses testing of the impact on the objective function, the impact of an element on gross rating points (GRPs) will also be assessed.

Therefore, the present study needs a pair of dependent variables to verify the model. To verify the model in terms of the impact on the objective function, the dependent variable for these analyses will be the adjusted gross rating points (AGRPs) which is a continuous variable. On the other hand, the model can also be tested in terms of the selection of the vehicles and their insertions. Here, the dependent variable will be the frequency of the vehicle insertions in the optimum schedule which is considered a categorical variable.

Analysis

The decision of the impact of any independent variable in the model should be made based on the results from the tests of both dependent variables (i.e., AGRPs and the frequency of vehicle selection). To illustrate, if the vehicle selection of the largest GRPs producing schedule from a model that incorporates a certain independent variable is quite different from the vehicle selection from a model that does not incorporate a

variable and if these two vehicle selections (i.e., schedules) estimate different AGRPs, the author will conclude that such an independent variable has an impact on the media selection process. In a case when the vehicle selection between the two treatments are different and the two schedules estimate similar AGRPs, such an independent variable is considered to have some impact on the media selection process but may be omitted for parsimony. Such a difference in vehicle selections does not damage the size of GRPs. More details will be presented in the following chapters.

Independent variables tested in this study have been determined based on the elements in the proposed media selection model (Figure 3, p. 63). These include timing of advertising, carryover effect, message effect, and media quantity discounts. The study has also decided to use a pair of control variables: the size of the advertising budget and the types of consumer magazines (i.e., low CPM magazine vs. high CPM magazine) which may have an indirect influence on the selection of the vehicles.

The data gathered from the optimization analysis were entered on a SYSTAT file for further statistical analysis. The data for dependent variables include the adjusted gross rating points (AGRPs), the simple gross rating points (GRPs), and the frequency of vehicle selection. The data for the vehicle type (i.e., low CPM vs. high CPM vehicle), the months (i.e., 1-6), and the size of advertising budget (i.e., high and low) were entered as control variables. The data of the independent variables were also inputted and these include the timing of advertising (i.e., long-term solutions vs. duplicated monthly optimum solutions), the use of media quantity discounts, the use and the degree of carryover effect (i.e., high, low and no carryover effect), and the use and the degree of message weights (i.e., high, low and no message effect).

The test of significance of each independent variable on the Adjusted GRPs

AGRPs will verify if a difference in the selection of the vehicles caused by the use of an independent variable will lead to a different media impact (i.e., adjusted gross rating points). To do so, the discussion initially will focus on the average value of AGRPs. This will provide a description of what effect the difference in the selection of the vehicles caused by the use of an independent variable made in terms of the value of AGRPs. Then, to see if such difference in AGRPs is statistically significant, analysis of variance (ANOVA) tests* were conducted.

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* The author will present the results of the significance of ANOVA based on a single factor ANOVA analysis. By doing so, the effect of each variable on the objective function can be isolated, thus the results will be easier to understand. In a situation where several variables are involved in this design, n-factor ANOVA might be an alternative to test the significance simultaneously, but the author believes the two analyses (i.e. one-way ANOVA and n-factor ANOVA) will lead to identical findings. First of all, in this study, the author does not expect interaction of any of the two independent variables. Thus, the interaction terms will not exist in the analysis of n-way ANOVA. In addition, the present study has applied the balanced design where each cell has an identical number of subjects. If these subjects are randomly assigned, the interfering effect of the other independent variables will be minimal in the analysis of single factor ANOVA. Finally, the examination of ANOVA formula will provide a better understanding of why the two analyses will lead to identical findings. The formula for ANOVA can be stated as follows:

$$F_{\text{in each treatment group}} = \frac{\text{between groups variance (Main Effect Mean Square)}}{\text{within groups variance (Mean Square Errors)}} \qquad (1)$$

The F score which is used to test the significance of the impact of each variable can be obtained by dividing the main effect mean square by mean square error. To see if the results of the significance of a variable from a single factor ANOVA is different from that from n-factor ANOVA, the author will compare the value of the main effect mean square and the value of the mean square error. These values can be obtained with the following formula:

$$\text{Main Effect Mean Square} = \frac{\text{Main Effect Sum of Squares}}{\text{degrees of freedom}} \qquad (2)$$

$$\text{Mean Square Errors} = \frac{\text{Errors Sum of Squares}}{\text{degrees of freedom}} \qquad (3)$$

$$\text{Total Sum of Squares} = \text{Sum of Groups Sum of Squares} + \text{Errors Sum of Squares} \qquad (4)$$

The main effect sum of squares in a treatment group equals the square of the deviation of a treatment group mean from the grand mean, which is the mean of the total sample. Since the grand mean, a treatment group mean, and the degrees of freedom of a treatment group do not change when we add additional variables to the design, the main effect mean square value in a treatment group will be identical in the two analyses. However, the errors sum of squares will vary depending on the choice of analyses. If we choose the n-factor ANOVA analysis, the value of the sum of main effect sum of squares will be larger due to additional main effects. Since the total sum of squares are the sum of main effect sum of squares and errors sum of squares (Equation 4), the size of the errors sum of squares

The test of significance of each independent variable on the selection of vehicles and their insertions will show whether the vehicle selections of the schedule that produces the largest GRPs from a model with an independent variable are different from those from a model without a variable. To do so, the present study first forms contingency tables of the frequency of vehicle insertions. These tables show the sum of the frequency of insertions recommended in all the optimum schedules related to a certain treatment group as well as the total percentage of each frequency. These tables will give a global view of the heterogeneity of the vehicle selections by comparing the solutions obtained from a model which examined a certain independent variable with the solutions obtained from a model which did not examine such variable. Then, to see if such heterogeneity is statistically valuable, Chi-square tests will be conducted since the dependent variable (i.e., frequency of vehicle insertions) in this validation is considered a nominal variable.

Concerning the levels of statistical significance which will be used to test ANOVA and Chi-square statistics, the present study has set the cut-off point at the .20 level. This is a rather broad significance level considering the fact that most advertising research uses the .15 level as the cut-off point, but the author believes this broad significance level is appropriate considering the purpose of this validation. All the independent variables tested in this chapter are conceptually important. If media selection is a simple process in which there are no difficulties involved in obtaining an

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will be smaller than that from a single factor ANOVA analysis. On the other hand, the size of the degrees of freedom will also be smaller due to additional factors. The size of the mean square errors will be quite similar in these two analyses (Equation 3). Therefore, the value of F score will be quite similar in these two analyses. To make sure the significances of a variable from these two analyses (i.e., a single factor ANOVA and n-factor ANOVA) are similar, the author will conduct n-factor ANOVA analyses. The results will be presented in the later chapter where appropriate.

optimum solution, the author recommends that all these variables be included in the model. Yet, since such a simple process is far from reality, the present study analyzes which, if any, of these independent variables have little impact on the media selection process. If so, those variables can be omitted for the parsimony of the media selection model. To omit any variable in the model, the author should have enough evidence of the variable's ineffectiveness on the media selection process. Therefore, a rather broad significance interval is more appropriate in this analysis.

Media Environment and Target Audience

As stated earlier, the present research will conduct the verification of the model under the framework of consumer magazines media data for a national and general brand that has neither seasonal nor geographic variations. In addition, to provide a realistic situation, two target markets are selected: female adults and male adults. The reasons for using a female target market and a male target market over the typical adult target markets in this research are that the audience of consumer magazines tend to be very selective and gender-skewed. Therefore, it will be more realistic to set up a narrower target environment instead of having a broader target market for consumer magazine advertising. According to SMRB (1988), the size of the target audience for female adults was 92,184,000 and that for male adults was 84,066,000. So, the first half of the analyses (=360) will be conducted with the target market of female adults, while the second half (=360) will be conducted with that of male adults. For each target group, the top 30 rated consumer magazines for both male and female target groups will constitute the sample pool for the present study. Consumer magazines

used for this study will be selected from SMRB (Appendix C).

This study has used these two target markets to produce more realistic optimum solutions and will not analyze the results based on the difference in target markets. This comparison of the optimum solutions by the difference in target markets would make the analysis more complex. If there is a certain reason to believe that the difference in target market is the key factor in determining the optimum solution, this study should report the findings of the effect of the target market variable, which can be a constraint variable in the media selection model. However, the author cannot find any reason to believe so. In fact, the difference of the optimization procedure in these two target markets are the differences in ratings and costs. Since this study applies 30 different magazine ratings and costs (i.e., a pair of magazines are selected from a pool of top 30 rated magazines) within each target market which will sufficiently consider the effect of the difference in ratings on the optimum solutions, the difference in target markets will not affect the outcome of the conclusions. Therefore, the findings based on the difference in target markets will be reported only if there is a significant difference in results from the two target groups.

Data Base

Table 4 presents the data base for the present study. Certainly, a larger number of the vehicles and the insertions would make a more comprehensive data base, but optimizing with this data base would require millions of options to be evaluated. This quantity of options makes even a single solution impossible. Considering the size of the problem, the data base for the present study will incorporate two vehicles: one with

two maximum insertions and the other with one maximum insertion. From a pool of the top 30 rated magazines in each target market, a pair of consumer magazines are randomly selected to constitute the data base. To select a random pair among the top 30 rated magazines, the Quick BASIC™ micro-computer program was used in this study. Between the two vehicles selected, the lower CPM vehicle is allowed to have two maximum insertions. This decision was based both on the findings from the Media Group (1989, p. 4-5) reporting that lower CPM vehicles had higher chance to be selected in the optimum schedule when optimizing GRPs, and on the understanding that the media planner would not buy a vehicle with higher CPM unless there is a special reason to do so. Therefore, the author thinks it would yield more realistic potential effects measures by allowing the lower CPM vehicle to have two maximum insertions.

Table 4
Data Base for the Study

	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Lower CPM Vehicle (2)	x	x	x	x	x	x
Higher CPM Vehicle (1)	x	x	x	x	x	x

Even this small data base would require the evaluation of 46,656 options for a single analysis. In a situation where no proven searching heuristics are available for the long-term optimization and where evaluating all the possible options would be the only way to get the optimum schedule, the present study will deal with a rather smaller data

base. A larger data base would be preferred, but the author in the study believes the analysis will be valid with the sophisticated research design.

End Effect

As explained earlier, the effects on advertising in the last three periods of the campaign will be carried over to the subsequent campaign period. This end effect should be included in the estimation of the present campaign in order to get a proper estimate of the impact of the present advertising. Therefore, the present model will consider the effects of this carryover effect.

On the other hand, the effects on advertising in the final three periods of the previous campaign will certainly be carried over to the present campaign period. Although this carryover effect should not be considered in the estimation of the impact on the present campaign, the amount of advertising in the early periods of the present campaign may be affected by the advertising in the previous campaign. For instance, if a brand has advertised heavily in a recent campaign, there may be no need to advertise in the early periods of the present campaign. Certainly, this end effect may affect the outcome of the optimum solution so that the model should consider this effect. The proposed model in this study will examine this effect.

However, a problem of determining the size of the previous advertising arises when the study adopts the hypothetical campaign. In practice, since the planner has information of this kind, he/she must incorporate this advertising in the estimation of the impact on the first three time periods of the present campaign. However, the present study cannot have this type of information. The amount of advertising in the last three time periods of the past campaign for the analysis of the present study must be

determined. Certainly, to test the end effect with the various amounts of advertising in these time periods may be desirable, but such testing would require more analysis. Since the purpose of the present analysis is to verify the elements in the model, the present study limits the scope of the analysis within that boundary and the exploration of the end effects will be left for the future study. In addition, since this study deals with the brand that does not have any seasonal and geographical variation, the amount of advertising across the time periods is expected not to have much variation. Therefore, the present study will assume that the amount of advertising for the last three months in the previous campaign period will be the same as that for the final three months in the present campaign period. There might be various ways of assuming the amount of advertising in the previous campaign periods, and different assumptions may lead to slightly different results. But, as explained earlier, to test various types of end effects may be beyond the scope of this study. The author believes that it is reasonable to assume that a brand advertised the same amount in the previous campaign as it does in the present period. To illustrate, the vehicle distributions in the present campaign will be a good choice for the past advertising if the vehicle distributions in the present campaign will be good enough to produce an optimal impact.

Research Hypotheses

Introduction

The author has developed the following hypothetical relationship to test the impact of each independent variable on the dependent variables. These research hypotheses are designed to test the effect of the four independent variables (i.e., timing

of advertising, message effect, carryover effect, and media quantity discounts) on the two dependent variables (AGRPs and the vehicle selection). The effect of an independent variable should be tested based on a pair of dependent variables. Therefore, this study has developed two research hypotheses to test the effect of each independent variable in the media selection process. As stated earlier, the findings of single hypothesis testing will not lead to the conclusion of the effect of an independent variable in the model. Rather, an estimation of the impact of any independent variable will be based on the combined results of a pair of hypotheses tests that are designed to test the effect of the same independent variable on different dependent variables. A total of 12 research hypotheses are presented in the following section.

Impact on the Objective Function (i.e., Adjusted Gross Rating Points)

Introduction

The goal of the test of the impact on the objective function is to determine the amount of GRPs for which the difference in vehicle selections between the two solutions could be responsible. This goal will be achieved by comparing the values of the Adjusted GRPs (AGRPs) between the treatment groups. The findings of the hypothesis testing on this dependent variable can be necessary information not only to make any conclusion about the impact of the independent variable in the media selection process, but also to provide the specific figures of the GRPs that are responsible for the effect of each independent variable.

Timing of advertising

Hypothesis 1. If all other factors are held constant for high and low budget levels, there will be no difference in the estimated impact between the solutions from the long-term optimization model and the solutions that suggest the most impact of the continuous advertising (i.e., aggregate monthly optimization).

If the estimated impact from a schedule that alternates vehicles across the time frame produces a significantly better impact than a schedule that suggests the most impact from continuous advertising (i.e., aggregate monthly optimization), the model should evaluate an option that alternates the vehicles over months. That evaluation is the function of a long-term optimization model. While the review of the literature showed that the timing of advertising is an essential element in the media planning process, only a few past media selection models had the capability of producing a long-term optimum solution as shown in Table 2 (pp. 31-32). Hypothesis 1 will test whether this element will make a significant impact on the value of the message GRPs. The gross rating points (GRPs) for the model that does not consider the timing of advertising could be obtained by evenly distributing a single month optimization schedule with one-sixth of the total advertising budget, and by considering other strategic elements such as media quantity discounts or carryover effect. If the objective function values from the long-term optimization model are no better than those from the model without timing option, there might be no reason to consider the option which makes the model very complex.

Message effect

Hypothesis 2. If all other factors are held constant for high and low budget levels, there will be no difference between the estimated value of adjusted gross rating

points (AGRPs) from the model that determines the optimum schedule based on vehicle gross rating points and the one from the model that determines the optimum schedule based on message gross rating points.

Hypothesis 3. If all other factors are held constant for high and low budget levels, there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from a model that applies the low message weights and the one from a model that applies the high message weights.

While the impact of the schedule should be estimated in terms of the exposure to the advertisement rather than the vehicle, many media planners seem to ignore such differences. In fact, about two thirds of the advertising agencies still estimate the impact of the schedule based on vehicle exposure (Kreshel et al., 1985; and Lancaster et al., 1986). In addition, a great number of past media selection models have failed to estimate message exposures after the vehicle exposures have been estimated (Table 2, pp. 31-32). Hypothesis 2 has been developed to test whether this element indeed makes a significant difference in the value of the objective function. In addition, the values of the message weights could be determined based both on the quality of the creative effort for that campaign and on those recognition and recall data as provided by syndicated services such as Starch and Gallup & Robinson. If the values of the message weights are not constant, the verification of the effects of different size weights on the value of the objective function becomes necessary. Hypothesis 3 has been developed to test such variances.

Media quantity discounts

Hypothesis 4. If all other factors are held constant for high and low budget levels, there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from the model that calculates the scheduling cost considering the media quantity discounts and the one from the model which calculates the cost without considering the media quantity discounts.

While the importance of accommodating the media quantity discounts into the media selection model has appeared in numerous past studies and media planning texts (e.g., Kaplan & Shocker, 1971; Scissors & Surmanek, 1982; and Jugenheimer & Turk, 1980), the review of past media selection models has shown that few of them have adopted this option (Table 2). Hypothesis 4 will test the importance of this element.

Carryover effect

Hypothesis 5. If all other factors are held constant for high and low budget levels, there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from the model that estimates the size of the GRPs in each schedule considering advertising carryover effect and the one from the model that estimates the size of the GRPs in each schedule without considering advertising carryover effect.

Hypothesis 6. If all other factors are held constant for high and low budget levels, there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from a model that applies the low carryover rates and the one from a model that applies high carryover rates.

In Chapter 2, the author has already discussed how the advertising exposure in a particular time period will be carried over to the subsequent period. In addition, the empirical findings have suggested that the size of the carryover rate can be determined based on various types of creative factors (e.g., Laband, 1989; Underwood & Schultz, 1967; and Strong, 1914). These findings have also suggested that the size of the carryover rate on advertising exposures will vary depending on the amount of the exposures. The studies concerning the advertising repetition effects have also been reviewed. Based on past findings, the present model includes an equation on carryover effect that also considers the advertising repetition effects. The extent to which this element is significant in the estimation of the objective function is still unclear. Hypothesis 5 tests this effect. In addition, since the empirical findings suggest that the size of the carryover rates could vary depending on the several message factors other than the exposures themselves, the question of how different rates of carryover effect could affect the value of the objective function needs to be tested. Hypothesis 6 has been developed to test these different rates of carryover effect.

Selection of the Vehicles and their Insertions

Background

Although the correct estimation of the scheduling impact allows media planners to select the proper amount of advertising, the correct selection of the vehicles and their insertions allows them to generate the greatest impact given the fixed advertising budget. If the media selection model does not have the proper mechanism of estimating the schedule impact, obtaining the optimum schedule would be very difficult since the evaluation of the schedule would be based on the wrong estimation. Yet, the ultimate

goal of media selection models is to decide the combination of the vehicles and their insertions both of which will produce the maximum impact. In this sense, testing the elements in light of the vehicle selection is such a valuable task. The following hypotheses will test how each element in the model will make a difference in the selection of the vehicles and their insertions in addition to AGRPs. If omitting an element in the model does not differentiate the value of the objective function and the vehicle selection, the conclusion that the element does not impact the model is possible.

Timing of advertising

Hypothesis 7. If all other factors are held constant for high and low budget levels, there will be no difference in the selection of the vehicles and their insertions between the results from the long-term optimization model and the results that suggest the most impact of the continuous advertising (i.e., aggregate monthly optimization).

By definition, the solutions from the aggregate monthly optimization analysis provide the maximum GRPs schedule with continuous advertising. In other words, the amount of monthly advertising is identical throughout a six-month campaign in this solution. On the other hand, the long-term optimization model evaluates the options that have the different combinations of vehicles through months. This model is superior to the aggregate single month optimization model in that the long-term optimization model evaluates more options. This model may suggest the maximum GRPs schedule that has better media impact than the maximum GRPs schedule from an aggregate monthly optimization model has. A comparison of vehicle selections between the two groups may reveal the superiority of the long-term optimization model. If no difference in vehicle selections between the two solution groups is found (i.e., the long-term optimization model suggests the continuous advertising schedule), there will

be no reason to adopt the long-term optimization model which is far more complex than the aggregate single-month optimization model.

Message effect

Hypothesis 8. If all other factors are held constant for high and low budget levels, there will be no difference in the selection of the vehicles and their insertions between the results from the model without the message effect option and those from the model with the message effect.

Hypothesis 9. If all other factors are held constant for high and low budget levels, there will be no difference in the selection of the vehicles and their insertions between the results with the low message weights and those results with high message weights.

So far, the author has presented the importance of estimating the impact of the media schedule in terms of message exposure rather than in terms of vehicle exposure throughout this dissertation. The review of past media planning texts has confirmed this importance. So, the impact of the media schedule should be estimated in terms of its exposure to advertisement. However, this importance does not necessarily mean that this variable should be included in selecting the maximum GRP schedule. If the model suggests virtually the same media schedule regardless of the use of this variable in the model, the effect of this variable on the media selection process is difficult to determine. The size of the GRPs has been reduced proportionally with the application of the message effect so that the model selects the same media schedule as the model which estimates in terms of the vehicle GRPs. Whether this variable affects the vehicle

selection could be shown only through the comparison of the vehicle selections between the two treatment groups. Thus, these two hypotheses have been developed to find out if the message effect variable is indeed significant in vehicle selection stage.

Media quantity discounts

Hypothesis 10. If all other factors are held constant for high and low budget levels, there will be no difference in the selection of the vehicles and their insertions between the results from the model that applies the media quantity discounts and those from the model which does not.

Even though the examination of the media quantity discounts in the model will allow the schedule that purchases the fewer vehicles with more insertions more efficiency, the extent to what this variable is effective enough to select the different maximum GRP schedule is unknown. When all other variables are held constant, the inclusion of this variable makes the schedule with fewer vehicles and more insertions more promising. But, whether such an incentive is good enough to lead the model to select the schedule that suggests fewer vehicles and more insertions has yet to be proven. The test of this hypothesis will certainly show how different the largest GRP producing schedule can be if the model adopts this variable.

Carryover effect

Hypothesis 11. If all other factors are held constant for high and low budget levels, there will be no difference in the selection of the vehicles and their insertions between the results from the model that does not consider carryover effect and those from the model that does.

Hypothesis 12. If all other factors are held constant for high and low budget levels, there will be no difference in the selection of the vehicles and their insertions between the results with low carryover rates and those with high carryover rates.

These two hypotheses are designed to determine if the maximum GRP schedule with carryover effect is indeed different from the schedule without the carryover effect. The inclusion of this variable will certainly have a greater effect on the media impact on the schedule, but it does not necessarily indicate a different optimum schedule. This hypothesis is certainly a necessary condition for the effectiveness of this variable. If this condition has not been met (i.e., the optimum schedule is the same regardless of the use of this variable), the test of the impact of an element on AGRPs will be meaningless. In other words, if the vehicle selection of the two solutions are the same, there is no reason to expect that AGRPs between the two treatment groups will be different.

Procedures-- Summary

To verify the ideal media selection model, a micro-computer program was developed using the Quick BASIC™ micro-computer program (Appendix A). To run this model, the IBM 486 - 33 MHZ machine with a math co-processor was used. A personal computer is considered more manageable and handy than a main frame computer. The use of a mainframe computer will significantly reduce the computation time, but that reduction will not be enough to ease the complexities involved in the long-term optimization analyses. For instance, a data base consisting of two maximum insertions for both vehicles, which just adds a single insertion to the current data base,

will increase a total number of options to be evaluated to get an optimum solution of 531,441 from the current 46,656. To add to the problem, this increase in computation time would not provide much additional information for this study. Furthermore, the use of a mainframe computer would require more research funds and less freedom in research. Since the author believes a 33 MHZ machine is adequate to execute the current analyses, a micro-computer was chosen over a mainframe computer to conduct the current analyses. Average computation time per analysis was about 40 minutes with this machine.

Optimization analyses require audience data (i.e., single ratings and duplication ratios) and vehicle cost data. Audience data were obtained from SMRB (1989), and the top 30 rated vehicles for each target market were selected from this data (Appendix C). Standard Rates and Data Service (SRDS) provided the cost and media discount data for these top 30 vehicles. From a pool of 30 vehicles, a pair of vehicles was selected for each analysis. Once a user has entered ratings, costs, media discount figures, and the size of the target market, the computer program asks him/her to input the types of treatments the user plans for each analysis (e.g. the size of budget, the use of media quantity discounts, the use of time frame, etc.). After a user enters the required information, the model starts to optimize. In 40 minutes, the model produces the results (for sample results, see Appendix B).

Limitations

While a great deal of effort has been made to ensure that the model is as comprehensive as possible, the present study should leave ample room for further research.

First of all, the present study could not incorporate some factors, such as seasonality and geographic consideration. The present study assumes a typical brand which has no seasonality and no geographical variation. Certainly, the complexity of the problem forces the model to be as simple as possible so that only a few factors that are critical enough to affect the outcomes of the optimal solutions are incorporated into the present model. The consideration of these factors are welcome and makes the model more comprehensive but will not be critical enough to affect the outcomes of the solutions.

The present study also assumes that the brand will use a single type of message throughout the campaign. In practice, a single copy only lasts a few months so that it may be necessary to consider the impact of new copy within the long-term campaign that will certainly affect the global impact in a schedule. This message variation will not be a problem in the analyses of a four-month or six-month time frame, but may be a problem in the analyses of a 10 or 12 month time frame. However, the problem size and excessive computer processing time prohibit the inclusion of an additional variable. Since this variable is considered less important than the other variables such as media quantity discounts and carryover which are included in the model, the consideration of this variable will be left for future research.

For the same reason, the present study could only incorporate a mini-scale data base and single medium optimization. If possible, a comprehensive data base and multiple media optimization would be better, but these are beyond the capability of today's technology. Yet, the author believes even the mini-scale data base and single medium optimization analysis will provide much valuable information about this subject and will be a foundation for more advanced topics such as multiple media optimization. Considering the lack of past research in this subject, the author believes the present

study will be a good starting point in exploring the nature of the long-term optimization process.

CHAPTER 6
RESULTS: OBJECTIVE FUNCTION (AGRPs)

Overview

Gross rating points (GRPs) are mainly obtained from the estimation of the frequency distribution using the beta binomial distribution model. Throughout the estimation process, either a weighting scheme or an array of mathematical equations, which are consistent with current empirical findings on each subject, are loaded to consider independent variables in this study. The procedure for obtaining the value of GRPs has been illustrated in Chapter 4.

However, GRPs estimated from the optimization model cannot directly be used in testing hypotheses due to the effect of the variable message and carryover weights. A main interest in this study concerning the value of the objective function is to know if the use of an independent variable makes a difference in the selection of an optimum schedule and if such difference in the selection of the schedule will lead to the difference in GRPs. Since this validation employs various sizes of message weights and those of carryover weights to test these independent variables and since these variable weights can also affect the value of GRPs, it is not desirable to compare GRPs estimated from the model for the present validation. So, the author has decided to sort out such effects by employing a new concept, adjusted gross rating points (AGRPs). The procedures and rationales for using AGRPs have been illustrated in Chapter 5.

Therefore, the present study will focus on AGRPs, the one re-estimated with constant carryover and message weight, in testing the research hypotheses of the impact

on the objective function. To do so, the present study first analyzes the mean of adjusted gross rating points (AGRPs) among treatment groups to see the size of the difference caused by each independent variable. To determine the statistical significance of an independent variable in the adjusted gross rating point, this study applies the differential statistical test, ANOVA. The statistical test results, along with the analyses of the impact on the vehicle selection, provide the empirical support on the use of each independent variable in the optimization analysis.

Although gross rating points will not be used in the test of impact on objective function, this fact does not mean that the concept of GRPs is completely useless in this study. First, the media selection model selects the largest GRP producing schedule by comparing the value of GRPs, not AGRPs, of each alternative. In addition, GRPs are more realistic estimations of media impact that the media planners will use than are those estimations of AGRPs.

Of importance to this study is the situation where the use of an independent variable makes a difference in the value of GRPs while it makes no difference in the value of AGRPs. Since the use of a variable does not make any difference in the value of AGRPs, there is no need to embrace that independent variable in selecting the maximum GRP schedule. However, if the use of a variable makes a difference in the value of GRPs, which means the omission of a variable from a model will lead to an incorrect estimation of media impact, the current study recommends that the model evaluates all the possible options without examining this variable (since it does not affect the vehicle selection of the optimum schedule) and re-estimates the value of GRPs after the optimization analysis to reduce the computation time. Then, even though the analyses of GRPs do not affect the decision in hypotheses testing, these analyses will provide the valuable information in developing a better media selection

model. So, this chapter reports the findings of the analyses of gross rating points (GRPs) in this chapter.

Timing of Advertising

This study questions, in relation to this independent variable, whether the optimization model should evaluate alternatives in which vehicles are alternated through different months as well as alternatives in which a monthly optimum schedule is used month after month. If the model does not have this timing dimension, a model user may develop a single month optimum schedule and use this schedule month after month. In a situation where most media researchers emphasized the importance of allocating the advertising budget through months in media planning, the model should consider this variable. Yet, whether or not this independent variable really makes any impact on the media selection process is unknown. The model that evaluates the schedules in which vehicles are alternated through different months has been termed the long-term optimization model. If the long-term optimization model improves the schedule impact, a true media selection model should incorporate the timing dimension into the model and increase the number of alternatives that the model should evaluate. If the long-term model does not improve the schedule impact, a single-month optimization schedule can be used repeatedly. Therefore, in the media selection model perspective, the decision of the test of timing of advertising will indicate the complexity of the better media selection model and the amount of time a model requires to get the schedules producing the largest GRPs. If the optimum solutions from the long-term optimization model do not produce larger Adjusted GRPs (AGRPs) than the schedules

in which duplicated monthly optimization schedules do, then developing a comprehensive media selection model can be much easier.

On the other hand, the subject of the timing of advertising can also be seen as the debate about the effectiveness of continuous advertising vs. the effectiveness of flighting advertising in the theoretical perspective. The solutions in which the single month optimization schedule is duplicated can be considered the continuous schedule where there is no difference in the amount of advertising through months. If the long-term optimization solution and the duplicated single month optimization solution are similar, this similarity supports the belief that continuous advertising is superior to the flighting schedule in a situation where no seasonality is involved. Otherwise, the flighting schedule will be better. In Chapter 2, the review of literature has shown that the findings have been inconclusive. The author believes that this validation could help answer this question.

A total of 720 solutions were used to test which of the two models, the long-term optimization model or the model that optimizes within a month and duplicates the monthly optimum schedule to form the long-term optimum schedule, suggests the optimum schedule that generates larger adjusted gross rating points (AGRPs). These 720 solutions were split into two groups to control the size of the budget. One half of the 720 solutions were obtained through the long-term optimization analysis, while the other half were obtained through monthly optimization analyses which do not incorporate a time frame. Table 5 and Table 6 show the statistical results of the use of time frame on the objective function.

At the high budget levels, the mean values of AGRPs in the solutions from the model that evaluated schedules in which vehicles were alternated (142.5) were higher than those values from the model that evaluated optimum schedules obtained through

Table 5
Statistical Comparison between the Impact of the Long-term Optimum Schedules Vs. the Impact of the Continuous Advertising Optimum Schedules at the High Budget Levels

Independent Variable: Timing of Advertising	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points*
		Mean	Mean
Impact of the Long-term Optimum Schedules	180	144.7	142.5
Impact of the Continuous Advertising Optimum Schedules	180	104.0	100.4

* This index value has been obtained after the optimization analysis. The model has selected the largest GRP producing schedule with the variable message and carryover weights. Then, with the optimum schedule produced from the model with variable weights, GRPs were re-estimated with the constant weights across the optimum schedules to neutralize the effect of the difference in the size of weights. The constant message weight was .5 and the constant carryover weight was .45.

	d.f.	M.S.	F	P
Timing of Advertising**	1	158,856.6	30.8	0.0

** ANOVA tests for a difference between the two schedules in Adjusted Gross Rating Points.

Table 6
Statistical Comparison between the Impact of the Long-term Optimum Schedules Vs. the Impact of the Continuous Advertising Optimum Schedules at the Low Budget Levels

Independent Variable: Timing of Advertising	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points
		Mean	Mean
Impact of the Long-term Optimum Schedules	180	103.0	98.1
Impact of the Continuous Advertising Optimum Schedules	180	70.4	66.8

	d.f.	M.S.	F	P
Timing of Advertising	1	88,068.8	28.7	0.0

the duplication of the monthly optimum schedules (100.4). These two figures were not significantly changed in the comparison of simple GRPs as Table 5 shows. The ANOVA test on this adjusted gross rating points (AGRPs) shows that this difference is considered to be significant at the .01 level .

As Table 6 shows, AGRPs in the optimum schedules from long-term optimization models (98.1) were also higher than those from duplicated monthly optimization solutions (66.8) at the low budget levels. This difference is statistically significant at the .01 level . The result also indicates that the values of GRPs are not much different from those of AGRPs (103 vs. 70.4).

In summary, although the decision of the necessity of an independent variable in the model can only be determined after both the test of the impact on the objective function and the test of the impact on vehicle selection, it is clear that the model generates a solution that has a larger value of AGRPs by examining schedules in which vehicles are alternated through different months[a] . On the other hand, the test of GRPs could show whether the model needs this variable to have a correct estimation of

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[a] To see if the findings of the significance of the timing of advertising variable on AGRPs do not vary when all the other independent variables are involved in ANOVA analysis, n-factor ANOVA analyses have been conducted. The results are presented.

1. N-factor ANOVA to test the Timing of Advertising Variable at the High Budget Levels.

	d.f.	M.S.	F	P
Timing of Advertising	**1**	**158,856.6**	**30.8**	**0.0**
Message Effect	2	5,425.6	1.1	0.4
Carryover Effect	2	4,737.2	0.9	0.4
Media Discounts	1	4,969.2	1.0	0.3

2. N-factor ANOVA to test the Timing of Advertising Variable at the Low Budget Levels.

	d.f.	M.S.	F	P
Timing of Advertising	**1**	**88,068.8**	**28.6**	**0.0**
Message Effect	2	2,711.3	0.9	0.4
Carryover Effect	2	1,738.5	0.6	0.6
Media Discounts	1	814.5	0.3	0.6

GRPs. As justified earlier, the model does not necessarily employ such independent variables in evaluating schedule alternatives unless these variables affect the vehicle selections. Yet, a significant impact of a variable on GRPs asks the model to re-estimate GRPs after the model has evaluated all the possible alternatives without considering that variable, if the variable has no affect on the selection of the vehicle to reduce the computation time.

Message effect

Use of Message Effect

In Chapter 2, the review of literature has shown that media planners should consider creative factors such as emotional appeal, involvement, immediacy, message complexity, and the quality of the message not only in determining the choice of media but also in estimating the correct media impact. The consideration of message effect is important in media planning because media planners always want to know the extent to which the target audience of their brand is exposed to their message rather than to the magazine. Since the syndicated data services publish the ratings and the duplication data in terms of the percentage of people exposed to the vehicles rather than to the advertisements, the estimation of the scheduling impact based on this data without having any adjustment mechanism can end up with the vehicle estimation, which is not of main interest to the advertiser. In addition, most past media selection models have not evaluated schedule alternatives based on the message impact (Table 2, pp. 31-32). In a situation where the most media planners acknowledge the importance of the message effect in media planning but few media models adopt this effect in the model,

the present study asks if the estimation of the schedule in terms of the message impact would have an effect on the selection of the vehicle and insertion configuration in the maximum GRP schedule. To test this variable, the current study has developed a mechanism to adjust vehicle estimation into message estimation, and the procedure for estimating message GRPs has been illustrated in Chapter 4.

As stated earlier, to test the independent variables other than the timing of advertising variables, only the optimum schedules from the long-term optimization model will be analyzed. The results from a total of 360 long-term optimum solutions were analyzed to validate the impact of choosing the largest GRP producing schedule with message GRPs. A third of these 360 long-term optimum solutions selected the largest GRP producing schedule using a model that applies the high message weights (= .6), another third selected the optimum schedule using a model that applies the low message weights (= .4), and the remaining third evaluated schedule alternatives with vehicle GRPs (i.e., no message weights). Therefore, each treatment group represented a total of 120 solutions. Finally, to control the impact of the size of the advertising budget, one half of the analyses conducted in this study selected the optimum schedule with a higher advertising budget and the other half selected the schedule with a lower advertising budget (Figure 7, p. 94).

The present study focuses on testing the impact of the use of the message effect variable if the application of message weight in estimating GRPs would affect the selection of vehicles. The analyses conducted with high message weight and those conducted with low message weight should be combined to represent the treatment group in which the schedule producing the largest GRPs was selected with message GRPs. The question of how the different sizes of the message weights will affect the selection of vehicle will be analyzed in the next chapter. Therefore, in each budget

level, a group in which message GRPs were used to select the optimum schedule contained 120 solutions, while a group in which vehicle GRPs were used to select the optimum schedule had 60 solutions. Table 7 and Table 8 list the statistical results of the use of message weights[b] .

By definition, the size of the media impact of vehicle exposure should be larger than the size of the media impact of message exposure. In other words, the size of the audience exposed to the magazine is certainly larger than the size of the audience exposed to a specific advertisement in the magazine. This fact is indicated by GRPs in Table 7. The average number of GRPs of the optimum solutions, when a model used the vehicle GRPs to select the maximum GRP schedule, is larger than the average number of GRPs when a model used the message GRPs (199.9 vs. 117.1) at the high budget levels. At the low budget levels, the findings that the average GRPs when a model estimated the vehicle GRPs to compare the schedule alternatives is significantly larger than the average GRPs when a model used the message GRPs, as Table 8

[b] To see if the findings of the significance of the use of message effect, carryover effect, and media quantity discounts variables on AGRPs do not vary when they are analyzed simultaneously in ANOVA analysis, n-factor ANOVA analyses have been conducted. Since the impact of the independent variables other than the timing of advertising variable has been analyzed with the long-term optimum solutions, the timing of advertising variable was not included in this n-factor ANOVA analysis. The results are presented.

1. N-factor ANOVA to test the Use of Message Effect, Carryover Effect, and Media Quantity Discounts at the High Budget Levels.

	d.f.	M.S.	F	P
Use of Message Effect	1	14,117.6	2.14	0.145
Use of Carryover Effect	1	52.1	0.01	0.929
Media Discounts	1	13,872.4	2.11	0.149

2. N-factor ANOVA to test the Use of Message Effect, Carryover Effect, and Media Quantity Discounts at the Low Budget Levels.

	d.f.	M.S.	F	P
Use of Message Effect	1	1,178.7	0.30	0.59
Use of Carryover Effect	1	15.8	0.004	0.95
Media Discounts	1	7,696.3	1.93	0.17

Table 7
Statistical comparison between the Largest Message GRP Producing Schedules Vs. the Largest Vehicle GRP Producing Schedules at the High Budget Levels

Independent Variable: Use of Message effect	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points*
		Mean	Mean
Impact of the Largest Message GRP Producing Schedules	120	117.1	148.7
Impact of the Largest Vehicle GRP Producing Schedules	60	199.9	129.9

* This index value has been obtained after the optimization analysis. The model has selected the largest GRP producing schedule with the variable message and carryover weights. Then, with the optimum schedule produced from the model with variable weights, GRPs were re-estimated with the constant weights across the optimum schedules to neutralize the effect of the difference in the size of weights. The constant message weight was .5 and the constant carryover weight was .45.

	d.f.	M.S.	F	P
Use of Message effect**	1	14,117.6	2.14	.145

** ANOVA tests for a difference between the two schedules in Adjusted Gross Rating Points.

Table 8
Statistical comparison between the Largest Message GRP Producing Schedules Vs. the Largest Vehicle GRP Producing Schedules at the Low Budget Levels

Independent Variable: Use of Message effect	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points
		Mean	Mean
Impact of the Largest Message GRP Producing Schedules	120	79.2	99.9
Impact of the Largest Vehicle GRP Producing Schedules	60	150.5	94.9

	d.f.	M.S.	F	P
Use of Message effect	1	1,178.7	.30	.59

shows (150.5 vs. 79.2). Comparing the media impact in terms of GRPs between the two treatment groups shows that a model cannot estimate correct GRPs without considering this variable. If the model which estimates the vehicle GRPs and the model which estimates the message GRPs suggest the same media schedule, a significant difference in GRPs suggests that a model should re-estimate the media impact after the model selects the optimum schedule with the vehicle GRPs to simplify the computer algorithm. However, this does not indicate whether the use of the message effect in the model affects the selection of the optimum solution.

The test of impact of the use of the message effect variable can be validated from the findings of the test of difference in Adjusted GRPs (AGRPs) and of the test of the difference in the vehicle selections and vehicle insertions. This chapter reports the significant at the .15 level . At the low budget levels, the present study has also found findings of the former test. As Table 7 shows, the AGRPs of the optimum solutions chosen from a model in which message GRPs were estimated to compare the schedule alternatives are higher than AGRPs of the optimum solutions chosen from a model in which vehicle GRPs were estimated to compare the schedule alternatives at the high budget levels (148.7 vs 129.9). This amount of difference in AGRPs was statistically the similar result (99.9 vs. 94.9) as Table 8 shows. But, this difference in Adjusted GRPs (AGRPs) was not statistically significant. As explained earlier, AGRPs are estimated through the re-estimation of the GRPs with the constant message and carryover weight after the largest GRP producing schedule has been chosen with GRPs from the optimization analysis to neutralize the effect of the size difference in these weights. Therefore, the difference of these AGRPs is attributable to the difference of vehicle selection between the optimum solutions from a model with message effect and those from a model without message effect. The test of the impact of the message

effect on AGRPs indicates that this independent variable affects the media selection at the high budget levels. Yet, the test of the impact on the vehicle selection should also support these findings before the present study makes any decision on the use of any independent variables in the model. On the other hand, although Table 7 and Table 8 indicate that the solutions obtained with message GRPs generated larger AGRPs than the solutions selected with vehicle GRPs, the cause of this difference is difficult to discover due to the complex estimation procedures involved in the media selection process.

Degree of Message Weights

Among the readers of a magazine, the constant percentage of people who read a specific advertisement in a magazine cannot be answered. As the review of literature in Chapter 2 reveals, the size of this message weight can only be determined based on creative factors such as emotional appeal, involvement, immediacy, message complexity, and the quality of the message. Since these factors could vary depending on the specific advertising situation, it was not desirable to use a constant message weight to test the impact of the use of the message effect on the media selection process in this study. This validation process applies two different levels of message weights in this verification process.

A main reason for applying various levels of the message weights is to control the effect of the size of message weight in testing the effect of examining the message effect on the media selection process. In other words, even if the test with a constant message weight shows that the evaluation in terms of the message effect is important in the media selection process, the question would remain if the test with different size of

the message weight also supports the findings. In addition, the information concerning the influence of different sizes of message weights on the selection of the maximum GRP schedules will also be helpful in figuring out the nature of the media selection process. If the models which estimate the GRPs of the schedule with the various sizes of message weights suggest the same optimum schedule, then the model users and the model builders do not have to worry about the size of the message weights and any reasonable size of message weights should lead to the optimum schedule. If this is not the case, then, the model users should assess the accurate message weight in order to obtain the largest GRP producing schedules for a certain campaign. Any wrong estimation of the message weight for the campaign should lead to the incorrect suggestion of the optimum schedule if the size of the message weight affects the selection of the vehicle in this test.

A total of 240 solutions were obtained from a long-term optimization model with message effect. Among these 240 solutions, one half of them were obtained after the model estimated the schedule impact (i.e., GRPs) with high message weight (= .6) while the other half were obtained with low message weight (= .4). Each treatment cell contains 60 solutions. Statistical results for this analysis are shown in Table 9 and Table 10[c].

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[c] To see if the findings of the significance of the degree of message weights variable on AGRPs do not vary when all the other independent variables are involved in ANOVA analysis, n-factor ANOVA analyses have been conducted. Since the impact of the independent variables other than the timing of advertising variable has been analyzed with the long-term optimum solutions, the timing of advertising variable was not included in this n-factor ANOVA analysis. The results are presented.

1. <u>N-factor ANOVA to test the Degree of Message Weights Variable at the High Budget Levels</u>.

	d.f.	M.S.	F	P
Degree of Message Weights	**1**	**14,436.5**	**2.20**	**0.141**
Use of Carryover Effect	1	3,476.2	0.53	0.468
Media Discounts	1	6,919.0	1.05	0.307

1. <u>N-factor ANOVA to test the Degree of Message Weights Variable at the Low Budget Levels</u>.

Table 9
Statistical Comparison between the Impact of the Optimum Schedules with High Message Weight Vs. the Impact of the Optimum Schedules with Low Message Weight at the High Budget Levels

Independent Variable: Variable Message Weights	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points*
		Mean	Mean
Impact of the Optimum Schedules with High Message Weight	60	147.3	159.7
Impact of the Optimum Schedules with Low Message Weight	60	87.0	137.8

* This index value has been obtained after the optimization analysis. The model has selected the largest GRP producing schedule with the variable message and carryover weights. Then, with the optimum schedule produced from the model with variable weights, GRPs were re-estimated with the constant weights across the optimum schedules to neutralize the effect of the difference in the size of weights. The constant message weight was .5 and the constant carryover weight was .45.

	d.f.	M.S.	F	P
Variable Message Weights**	1	14,436.5	2.21	0.14

** ANOVA tests for a difference between the two schedules in Adjusted Gross Rating Points.

Table 10
Statistical Comparison between the Impact of the Optimum Schedules with High Message Weight Vs. the Impact of the Optimum Schedules with Low Message Weight at the Low Budget Levels

Independent Variable: Variable Message Weights	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points
		Mean	Mean
Impact of the Optimum Schedules with High Message Weight	60	94.6	98.9
Impact of the Optimum Schedules with Low Message Weight	60	63.8	100.8

	d.f.	M.S.	F	P
Variable Message Weights	1	104.2	.02	0.88

message weight was applied) are almost the same at the low budget levels (Table 10). The ANOVA test[c] indicates that the various sizes of message weights have no affect on the value of the AGRPs at these budget levels. Once again, the test of the impact of this independent variable on the selection of vehicles should be followed before the present study makes any conclusion of the impact of this variable.

On the other hand, the comparison of the mean values of GRPs shows that a correct estimation of the message weight is essential in estimating correct GRPs of the optimum schedule (Table 9 and Table 10). The model in which higher message weight is applied estimates significantly higher GRPs than does the model in which lower message weight is applied at both budget levels (i.e., 147.3 vs. 87 at the high budget levels, and 94.6 vs. 63.8 at the low budget levels).

Media Quantity Discounts

Despite a general acknowledgement of the importance of quantity discounts in media selection in past literature, only a few past media selection models have

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[c] To see if the findings of the significance of the degree of message weights variable on AGRPs do not vary when all the other independent variables are involved in ANOVA analysis, n-factor ANOVA analyses have been conducted. Since the impact of the independent variables other than the timing of advertising variable has been analyzed with the long-term optimum solutions, the timing of advertising variable was not included in this n-factor ANOVA analysis. The results are presented.

1. N-factor ANOVA to test the Degree of Message Weights Variable at the High Budget Levels.

	d.f.	M.S.	F	P
Degree of Message Weights	**1**	**14,436.5**	**2.20**	**0.141**
Use of Carryover Effect	1	3,476.2	0.53	0.468
Media Discounts	1	6,919.0	1.05	0.307

2. N-factor ANOVA to test the Degree of Message Weights Variable at the Low Budget Levels.

	d.f.	M.S.	F	P
Degree of Message Weights	**1**	**104.2**	**0.02**	**0.882**
Use of Carryover Effect	1	2,140.2	0.45	0.502
Media Discounts	1	9,013.3	1.91	0.170

incorporated this variable. Most models did not incorporate this variable because the accommodation of this variable makes the model more complex. In their work, Kaplan & Shocker (1971) indicated this practice by stating that "the existence of media quantity discounts introduced difficulties that would prohibit a purely mathematical programming approach from reaching an optimal solution even with a non-linear effective function." In fact, the discount structure in the consumer magazine industry is too diversified to be generalized. Yet, it seems certain that the application of media quantity discounts enables the model to evaluate the schedules with more magazines by reducing the unit cost of the magazine. It is very likely that the model with discounts selects the optimum schedule with more magazines than does the model without discounts. If the use of media quantity discounts affects the selection of vehicles, the validity of the solutions from the media selection model that does not accommodate the discounts will be questionable. This chapter reports the results of the impact of the use of media quantity discounts on the Adjusted GRPs (AGRPs).

Among a total of 360 optimum solutions analyzed for this variable, one half represents the results from a model that applies the media quantity discounts in calculating the total cost of each alternative while the other half represents the results from a model that applies the fixed unit cost of each magazine. In addition, the results were split into two groups to control the size of the budget. Thus, each treatment group contains 90 solutions. Table 11 and Table 12 provide the statistical results for this analysis.

The results indicate that the application of the media quantity discounts has an affect on the value of the Adjusted GRPs (AGRPs) at both budget levels. In other words, the model considering the media quantity discounts suggests the optimum schedule with larger AGRPs than does the model that did not consider the discounts.

Table 11
Statistical Comparison between the Impact of the Optimum Schedules from a Model with Media Quantity Discount Option Vs. the Impact of the Optimum Schedules from a Model without Media Quantity Discount Option at the High Budget Levels

Independent Variable: Media Quantity Discounts	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points*
		Mean	Mean
Impact of Optimum Schedules from a Model with Media Discount Option	90	153.2	151.2
Impact of Optimum Schedules from a Model without Media Discount Option	90	136.2	133.7

* This index value has been obtained after the optimization analysis. The model has selected the largest GRP producing schedule with the variable message and carryover weights. Then, with the optimum schedule produced from the model with variable weights, GRPs were re-estimated with the constant weights across the optimum schedules to neutralize the effect of the difference in the size of weights. The constant message weight was .5 and the constant carryover weight was .45.

	d.f.	M.S.	F	P
Media Quantity Discounts**	1	13,872.4	2.10	0.149

** ANOVA tests for a difference between the two schedules in Adjusted Gross Rating Points.

Table 12
Statistical Comparison between the Impact of the Optimum Schedules from a Model with Media Quantity Discount Option Vs. the Impact of the Optimum Schedules from a Model without Media Quantity Discount Option at the Low Budget Levels

Independent Variable: Media Quantity Discounts	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points
		Mean	Mean
Impact of Optimum Schedules from a Model with Media Discount Option	90	108.5	104.6
Impact of Optimum Schedules from a Model without Media Discount Option	90	97.4	91.5

	d.f.	M.S.	F	P
Media Quantity Discounts	1	7,696.3	1.95	0.16

At the high budget levels, the average AGRPs of the solutions from a model with media quantity discounts are 151.2 while that of the solutions from a model without media quantity discounts are 133.7 (Table 11). This difference between the two treatments was statistically significant at the .15 level . At the low budget levels, the similar findings have also been obtained. The difference in AGRPs between the two treatments of 13.1 was statistically significant at the .20 level (Table 12).

Carryover Effect

Use of Carryover Effect

One of the complexities involved in developing a long-term media selection model which suggests the long-term media plan is the consideration of the effect of advertising in the past month carried over to the present month. In other words, the long-term model should not only evaluate the schedule alternatives in which vehicles are alternated through different months, but also consider advertising carryover effect which was not considered in single-month optimization model, making the model more comprehensive but complex. In Chapter 2, the present study has shown that the carryover effect can have many different meanings in advertising research. Since the objective function of the present study is gross rating points (GRPs) which can be obtained through the estimation of exposure frequency distribution, the meaning of carryover effect in the present study should be the carryover effect of advertising exposure. The focus of this validation of carryover effect in this media selection model is on the process by which the effect of the advertising exposure in one month will be carried over to the subsequent month. The current study has shown the importance of

the carryover effect on advertising exposure in media planning and has determined that the carryover effect should be one of the important strategic variables in the media selection model in Chapter 2.

In this model validation, the present study will show if the consideration of the carryover effect on advertising exposure in the model will affect the media selection process in the model. In estimating a schedule impact, the consideration of this carryover effect seems to be desirable, but will create more complexities in the model. Yet, if the consideration of the carryover effect affects the selection of vehicles, the model should examine this variable in estimating the media impact (i.e., gross rating points).

To see if accommodation of the carryover effect influences the value of the objective function (i.e., AGRPs), a total of 360 analyses, the results from long-term optimization analyses were used to uncover the impact of carryover effect on Adjusted GRPs (AGRPs). Like the test of the impact of the use of the message effect variable, two thirds of these 360 analyses (i.e., 240 analyses) selected the optimum schedule from a model which considered carryover effect in estimating GRPs. The remaining 120 solutions were obtained from a model which did not consider carryover effect. These 360 results were split into two groups to control the difference in the degree of budget levels.

Table 13 and Table 14 show the statistical findings of the effect of applying carryover effect in estimating the media impact. By definition, the size of the media impact of the optimum schedule from a model that has applied the carryover effect in estimating GRPs should be larger than the size of the media impact of the optimum schedule from a model that has not applied the carryover effect. These results are

Table 13
Statistical Findings of the Effect of Applying Carryover Effect in Estimating the Media Impact at the High Budget Levels

Independent Variable: Carryover Effect	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points*
		Mean	Mean
When Carryover Effect is applied into the Model	120	170.4	142.1
When Carryover Effect is not applied into the Model	60	93.4	143.2

* This index value has been obtained after the optimization analysis. The model has selected the largest GRP producing schedule with the variable message and carryover weights. Then, with the optimum schedule produced from the model with variable weights, GRPs were re-estimated with the constant weights across the optimum schedules to neutralize the effect of the difference in the size of weights. The constant message weight was .5 and the constant carryover weight was .45.

	d.f.	M.S.	F	P
Carryover Effect**	1	52.1	0.01	0.93

** ANOVA tests for a difference between the two schedules in Adjusted Gross Rating Points.

Table 14
Statistical Findings of the Effect of Applying Carryover Effect in Estimating the Media Impact at the Low Budget Levels

Independent Variable: Carryover Effect	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points
		Mean	Mean
When Carryover Effect is applied into the Model	120	120.4	98.3
When Carryover Effect is not applied into the Model	60	68.2	97.6

	d.f.	M.S.	F	P
Carryover Effect	1	15.8	0.004	0.95

shown in Table 13 and Table 14. At both budget levels, the gross rating points (GRPs) of the optimum solutions from a model that applied the carryover effect were significantly larger than those from a model that did not (e.g., 170.4 vs. 93.4 at high budget levels). However, the model re-estimated GRPs with constant message and carryover weight, in order to neutralize the effect of the difference in the size of carryover weight with the optimum solution recommended from a model with various carryover weights. The re-estimation found no difference between the two treatments at the high budget levels (142.1 vs. 143.2). At the low budget levels, the present study also found similar results (98.3 vs. 97.6). This difference, while not statistically significant, offers partial support of the fact that the model which considers the carryover effect in estimating GRPs does not suggest a vehicle and insertion selection different from that of the model without carryover effect. As stated, more analysis is necessary to make a conclusion. In summary, the use of carryover effect does not seem to have any impact on the value of the objective function.

Degree of Carryover Weights

The review of literature revealed that the amount of advertising exposure which will be carried over to the subsequent time period will be determined by factors such as meaningfulness of the stimuli, similarity of items, the size of the advertising message, and the levels of original learning. Therefore, applying a constant carryover rate in this verification process seems undesirable. To control the size of carryover effect in testing the impact of examining the carryover effect on the vehicle selection, this study used two different levels of carryover rate in this verification process. In the previous section, the current study analyzed the effect of the consideration of the carryover effect

in the estimation of GRPs. In this section, the present study will show the results of the effect of various levels of carryover rates on the vehicle selection of the schedules producing the largest GRPs.

To see the impact of the degree of carryover weights on GRPs, a total of 240 analyses were used. In each budget level, the results from a model with high carryover weights (N=60) were compared to the results from a model with low carryover weights (N=60). Table 15 and Table 16 show the results of statistical comparison between GRPs of the optimum schedules with high carryover weights vs. the GRPs of the optimum schedules with low carryover weights[d] .

As Table 15 shows, the mean value of AGRPs in the solutions from a long-term optimization model which selects the optimum schedules with high carryover weight (134.4) is lower than the value from the model which applied low carryover weight (149.8) at the high budget levels. However, this amount of difference in AGRPs between the two treatment was not statistically significant.. At the low budget

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[d] To see if the findings of the significance of the degree of carryover weights variable on AGRPs do not vary when all the other independent variables are involved in ANOVA analysis, n-factor ANOVA analyses have been conducted. Since the impact of the independent variables other than the timing of advertising variable has been analyzed with the long-term optimum solutions, the timing of advertising variable was not included in this n-factor ANOVA analysis. The results are presented.

1. N-factor ANOVA to test the Degree of Carryover Weights Variable at the High Budget Levels.

	d.f.	M.S.	F	P
Use of Message Effect	1	1,931.2	0.27	0.602
Degree of Carryover Weights	**1**	**7,110.2**	**1.01**	**0.318**
Media Discounts	1	7,468.7	1.06	0.306

2. N-factor ANOVA to test the Degree of Carryover Weights Variable at the Low Budget Levels.

	d.f.	M.S.	F	P
Use of Message Effect	1	5,048.1	1.24	0.269
Degree of Carryover Weights	**1**	**6,026.5**	**1.47**	**0.227**
Media Discounts	1	10,833.8	2.65	0.106

Table 15
Statistical Comparison between the Impact of the Optimum Schedules with High Carryover Weights Vs. the Impact of the Optimum Schedules with Low Carryover Weights at the High Budget Levels

Independent Variable: Variable Carryover Weights	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points*
		Mean	Mean
Impact of the Optimum Schedules with High Carryover Weight	60	180.8	134.4
Impact of the Optimum Schedules with Low Carryover Weight	60	160.0	149.8

* This index value has been obtained after the optimization analysis. The model has selected the largest GRP producing schedule with the variable message and carryover weights. Then, with the optimum schedule produced from the model with variable weights, GRPs were re-estimated with the constant weights across the optimum schedules to neutralize the effect of the difference in the size of weights. The constant message weight was .5 and the constant carryover weight was .45.

	d.f.	M.S.	F	P
Variable Carryover Weights**	1	7,110.2	1.01	0.32

** ANOVA tests for a difference between the two schedules in Adjusted Gross Rating Points.

Table 16
Statistical Comparison between the Impact of the Optimum Schedules with High Carryover Weights Vs. the Impact of the Optimum Schedules with Low Carryover Weights at the Low Budget Levels

Independent Variable: Variable Carryover Weights	Number of Optimum Schedules Analyzed	Gross Rating Points	Adjusted Gross Rating Points
		Mean	Mean
Impact of the Optimum Schedules with High Carryover Weight	60	132.8	91.2
Impact of the Optimum Schedules with Low Carryover Weight	60	107.9	105.4

	d.f.	M.S.	F	P
Variable Carryover Weights	1	6,026.5	1.45	0.23

levels, the results of the test of the effect of the various sizes of carryover weights on AGRPs are consistent with the results at the high budget levels. The average AGRPs among the optimum schedules from a model that estimated the media impact with high carryover weight (91.2) is lower than the value with low carryover weight (105.4) as Table 16 shows. This difference is not statistically significant. The test of the impact of this independent variable on the selection of vehicles should be followed before the present study makes any conclusions of the impact of this variable.

On the other hand, the comparison of the mean values of GRPs shows that a correct estimation of the carryover weight is essential in estimating correct GRPs of the optimum schedule (Table 15 and Table 16). Ideally, the model should incorporate any independent variable if such an independent variable affects the correct estimation of the media impact. However, the complexities involved in the media selection model prevent the model from incorporating such independent variables. For the parsimony of the model, only the variables that affect the selection of the optimum schedule will be incorporated. The significant impact of any independent variable (e.g., carryover effect) on the correct estimation of the media impact will force the model to re-estimate the media impact with that variable after the optimization analysis has selected the optimum schedule without that variable, if such an independent variable has no effect on the vehicle selection of the optimum schedule. The comparison of the mean values of GRPs will show that such re-estimation procedure is necessary in the optimization analysis. The results in Table 15 and Table 16 indicate that the model in which higher carryover weight is applied estimates a significantly higher GRPs than does the model in which lower carryover weight is applied at both budget levels (i.e., 180.8 vs. 160 at the high budget levels, and 132.8 vs. 107.9 at the low budget levels).

Summary

As stated, a main concern in the verification of any elements in the proposed media selection model is to determine whether the use of an element in the model makes a difference in the vehicle selection of the maximum GRP schedule and if such a difference in the vehicle selection will lead to the difference in media impact. The current chapter has reported the findings of the latter test which questions whether the difference in the vehicle selection leads to a difference in media impact. In the following chapter, the results of the test of the independent variables on vehicle selections will be reported.

The results show the presence of a significant impact of the timing of advertising variable and that of media quantity discounts variables on Adjusted GRPs at both budget levels. The results also indicate an effect of the use of message effect and of the size of the message weights on AGRPs at the high budget level. However, the current study has not reported any effect of carryover effect on AGRPs. Any conclusion of the impact of elements in the model should be drawn only after the test on vehicle selections has been conducted.

CHAPTER 7
RESULTS: VEHICLE SELECTION AND NUMBER OF INSERTIONS

Overview

This chapter will reveal the impact of each independent variable on vehicle selections in the optimization process. A significant impact of a certain independent variable (e.g., timing of advertising or message effect) on the selection of vehicles could mean that the optimization model which accommodates a certain independent variable will produce recommended solutions different from these solutions of the model without that independent variable. As stated earlier, the present study will conclude the effect of an independent variable on the media selection process based on the results from the test of the Adjusted GRPs (AGRPs) whose findings have been reported in the above section and on the results from the test of the vehicle selection whose findings will be reported in this section.

To test the difference in impact on the selection of vehicles and their insertions for each independent variable, the present study provides the summary of the vehicle selection of the maximum GRP schedules. To discover the effect of each independent variable on the selection of vehicles and their insertions, this study reports two contingency tables: one for the summary of optimum schedules from a model that included a certain independent variable (e.g., in the test of the timing of advertising variable, this summary represents the long-term optimum schedules), and the other for the summary of optimum schedules from a model that did not included a certain independent variable (e.g., in the test of the timing of advertising variable, this

summary represents the schedules in which a monthly optimization schedule is duplicated month after month). Each summary table follows the format of the actual largest GRP-producing schedule of each optimization analysis. The row of the table represents the types of magazines used in this analysis. The present study has selected a pair of consumer magazines for each optimization analysis. Magazine 1 in the summary table represents the higher CPM magazine between the two magazines, while Magazine 2 represents the lower CPM magazine (e.g., Table 17). Each column of the table represents the number of months. For the verification of the model, the proposed media selection model suggests a six-month consumer magazine schedule. The rationales for adopting two magazines and a six-month media schedule in this study has been stated in Chapter 4. The raw numbers in the summary table represent the total of insertions of each magazine recommended in a specific time period from all the optimization analyses assigned to each treatment. For example, for the upper table in Table 17, which is the summary of vehicle selection for long-term optimum schedules, a total of 180 schedules were analyzed. The first upper cell of the upper table in Table 17 (= 92) represents the total number of insertions recommended for Magazine 1 in the first month from those 180 solutions. To know the distribution of the insertions among the optimum schedules, the total percentage figures have also been provided in the table. For example, the percentage figures in the first upper cell of the upper table in Table 17 (= 4.2) represent that 180 optimum solutions in total recommend 4.2 percent of a total 2,174 insertions for the higher CPM magazine in the first month. To see if this difference in the vehicle selections between the two tables is statistically significant, the results of Chi-square statistics have also been provided at the bottom of each table.

The analysis of the impact on the vehicle selection has been conducted by three

Table 17
Statistical Comparison of the Vehicle Selection for the Long-term Optimum Schedules Vs. the Vehicle Selection for the Continuous Advertising Optimum Schedules at the High Budget Levels

Vehicle Selection for Long-term Optimum Schedules[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	92 (4.2[c])	50 (2.3)	43 (2.0)	30 (1.4)	31 (1.4)	13 (0.6)	259 (11.9)
Magazine 2	352 (16.2)	339 (15.6)	342 (15.7)	331 (15.2)	312 (14.4)	239 (11.0)	1915 (88.1)
Total	444 (20.4)	389 (17.9)	385 (17.7)	361 (16.6)	343 (15.8)	252 (11.6)	2174[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 180 long-term optimum schedules. "Long-term optimum schedules" mean that the timing of advertising is considered in determining the largest GRP producing schedule.

[b] 2,174 represents a total number of magazines recommended from the total of 180 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 180 optimum solutions in total recommends 4.2% of a total 2,174 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for Continuous Advertising Optimum Schedules[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	45 (2.6)	45 (2.6)	45 (2.6)	45 (2.6)	45 (2.6)	45 (2.6)	270 (15.6)
Magazine 2	244 (14.1)	244 (14.1)	244 (14.1)	244 (14.1)	244 (14.1)	244 (14.1)	1464 (84.4)
Total	289 (16.7)	289 (16.7)	289 (16.7)	289 (16.7)	289 (16.7)	289 (16.7)	1734 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 180 continuous advertising optimum schedules. "Continuous advertising optimum schedules" mean that the timing of advertising is not considered in determining the largest GRP producing schedule.

Chi-Square Test Results for Long-term Optimum Schedules Vs. Continuous Advertising Optimum Schedules at High Budget Levels

Timing of Advertising	Degrees of Freedom	Value (χ^2)
Total Number of Vehicle Insertions	1	49.5*
Monthly Advertising Allocation of Optimum Schedules	5	27.1*
Vehicle Preference of Optimum Schedules	1	11.0*

* Significant at the .01 levels

tests: a test of the difference in the total number of vehicle insertions selected, a test of the difference in the selection of the magazines between the two tables (e.g., if the ratio of the selection of the two magazines in the long-term optimization schedules has been changed in the schedule in which a monthly optimum schedule is duplicated), and a test of the difference in the allocation of the insertions through the time period (e.g., if the preference of advertising in a certain time period in the long-term optimization schedules has been changed in the schedule in which monthly optimum schedule is duplicated). The test of the difference in the total number of vehicle insertions selected shows whether or not the accommodation of a certain independent variable allows the model to suggest more insertions in the maximum GRP schedule. Even when the two models suggest the same number of vehicle insertions, the two solutions can be said to be different if the ratio of the magazine selection between the two solutions are different. The same reasoning can be applied to the test of difference in the allocation of the vehicle insertions through various months. A significant difference in any of these three tests will lead to the conclusion that the two solutions are different.

Timing of Advertising

Table 17 shows the statistical comparison of the vehicle selection for long-term optimum schedules vs. the vehicle selection for the continuous advertising optimum schedules at the high budget levels. Long-term optimum schedules have been selected from a model that evaluates the options in which vehicles are alternated through months to consider the timing of advertising. Continuous advertising optimum schedules, on the other hand, have been obtained from a model that does not consider the various amounts of advertising through months such that a single-month optimization schedule

is duplicated month after month. While the long-term optimization model evaluates the media schedules in which different single month schedules are combined, a continuous advertising model mainly focuses on the optimization of a single-month schedule which will be duplicated to form a long-term media schedule.

To test the impact of the timing of advertising variable on vehicle selection, a total of 360 analyses have been conducted at the high budget levels. Among these, 180 solutions represent long-term optimum schedules while the other 180 solutions represent continuous advertising schedules. As Table 17 indicates, these 180 long-term optimum schedules have recommended a total of 2,174 insertions, while the continuous advertising optimum schedules have recommended a total of 1,734 insertions at the high budget levels. Chi-square statistics show that this difference in the total number of vehicle selections is statistically significant at the .01 level. In addition, the comparison of the difference in the selection of the magazines indicates that the long-term optimization model has suggested the lower CPM magazine (i.e., Magazine 2) more frequently than does the continuous advertising optimization model (88.1 percent vs. 84.4 percent). This difference is also statistically significant at the .01 level . Finally, a comparison of the difference in the allocation of the insertions through the time periods shows that the long-term optimization model has suggested heavy advertising in the earlier campaign period while the optimization model that does not consider the timing of advertising suggests continuous advertising. This difference is also statistically significant at the .01 level (Table 17). In summary, the vehicle and insertions selections of the optimum schedules from the long-term optimization model are different from the selections of the continuous advertising optimization model at the high budget levels.

The findings at the low budget levels on the impact of the timing of advertising variable on the selection of vehicles and their insertions are similar to the findings at the high budget levels (Table 18). The long-term optimization model has recommended more insertions (1,623 vs. 1,326), has suggested lower CPM magazine more frequently (91.2 percent vs. 84.2 percent), and has suggested heavier advertising in the earlier campaign period than does the duplicated single month optimization model. All of these differences are statistically significant at the .01 level . The findings at the low budget levels indicate that this timing of advertising variable has an impact on the vehicle selection, even for small media schedules. In conclusion, the media schedule developed from a single month optimization model cannot be close to the true optimum schedule no matter what size media schedule a planner develops.

Message Effect

Use of Message Effect

A main focus of the test of the use of message effect is on knowing if the evaluation of the media schedule in terms of the message GRPs rather than of the vehicle GRPs is important in the selection of the vehicle in the optimum solutions. Table 19 shows the statistical comparison of the vehicle selection of the largest message GRP producing schedules vs. the vehicle selection of the schedules producing the largest vehicle GRPs at the high budget levels. The largest message GRP producing schedules have been obtained from the evaluation of the size of the gross exposure to the advertisement while the maximum vehicle GRP schedules have been obtained from

Table 18
Statistical Comparison of the Vehicle Selection for the Long-term Optimum Schedules
Vs. the Vehicle Selection for the Continuous Advertising Optimum Schedules
at the Low Budget Levels

Vehicle Selection for Long-term Optimum Schedules[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	59 (3.6[c])	34 (2.1)	22 (1.4)	18 (1.1)	8 (0.5)	2 (0.1)	143 (8.8)
Magazine 2	340 (21.0)	318 (19.6)	298 (18.4)	244 (15.0)	172 (10.6)	108 (6.7)	1480 (91.2)
Total	399 (24.6)	352 (21.7)	320 (19.7)	262 (16.1)	180 (11.1)	110 (6.8)	1623[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 180 long-term optimum schedules. To obtain "Long-term optimum schedules", the timing of advertising is considered in determining the largest GRP producing schedule.

[b] 1,623 represents a total number of magazines recommended from the total of 180 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 180 optimum solutions in total recommends 3.6% of a total 1,623 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for Continuous Advertising Optimum Schedules[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	35 (2.6)	35 (2.6)	35 (2.6)	35 (2.6)	35 (2.6)	35 (2.6)	210 (15.8)
Magazine 2	186 (14.0)	186 (14.0)	186 (14.0)	186 (14.0)	186 (14.0)	186 (14.0)	1116 (84.2)
Total	221 (16.7)	221 (16.7)	221 (16.7)	221 (16.7)	221 (16.7)	221 (16.7)	1326 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 180 continuous advertising optimum schedules. "Continuous advertising optimum schedules" mean that the timing of advertising is not considered in determining the largest GRP producing schedule.

Chi-Square Test Results for Long-term Optimum Schedules
Vs. Continuous Advertising Optimum Schedules at Low Budget Levels

Timing of Advertising	Degrees of Freedom	Value (χ^2)
Total Number of Vehicle Insertions	1	29.9*
Monthly Advertising Allocation of Optimum Schedules	5	115.3*
Vehicle Preference of Optimum Schedules	1	34.2*

* Significant at the .01 levels

Table 19
Statistical Comparison of the Vehicle Selection for the Largest Message GRP Producing Schedules Vs. the Vehicle Selection for the Largest Vehicle GRP Producing Schedules at the High Budget Levels

Vehicle Selection for the Largest Message GRP Producing Schedules [a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	62 (4.3[c])	36 (2.5)	32 (2.2)	22 (1.5)	22 (1.5)	9 (0.6)	183 (12.6)
Magazine 2	235 (16.2)	224 (15.4)	229 (15.8)	219 (15.1)	208 (14.3)	155 (10.7)	1270 (87.4)
Total	297 (20.2)	260 (17.9)	261 (18.0)	241 (16.6)	230 (15.8)	164 (11.3)	1453[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 120 largest message GRP producing schedules. "Largest Message GRP Producing Schedules" mean that the gross rating points which is the benchmark for selecting an optimum solution was adjusted to reflect the advertising copy effect once the vehicle ratings were applied.

[b] 1,453 represents a total number of magazines recommended from the total of 120 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 120 optimum solutions in total recommends 4.3% of a total 1,453 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Largest Vehicle GRP Producing Schedules[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	30 (4.2)	14 (1.9)	11 (1.5)	8 (1.1)	9 (1.3)	4 (0.6)	76 (10.5)
Magazine 2	117 (16.2)	115 (16.0)	113 (15.7)	112 (15.5)	104 (14.4)	84 (11.7)	645 (89.5)
Total	147 (20.4)	129 (17.9)	124 (17.2)	120 (16.6)	113 (15.7)	88 (12.2)	721 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 largest vehicle GRP producing schedules. "Largest Vehicle GRP Producing Schedules" mean that the gross rating points which is the benchmark for selecting an optimum solution was not adjusted to reflected the advertising copy effect once the vehicle ratings were applied.

Chi-Square Test Results for the Largest Message GRP Producing Schedules Vs. the Largest Vehicle GRP Producing Schedules at High Budget Levels

Use of Message Effect	Degrees of Freedom	Value (χ^2)
Total Number of Vehicle Insertions	1	0.04
Monthly Advertising Allocation of Optimum Schedules	5	0.77
Vehicle Preference of Optimum Schedules	1	2.98*

* Significant at the .10 levels

** Other variables were not significant at the .20 levels

the estimation of the size of the gross exposure to the magazine. At a glance, one may notice that the solutions from a model that evaluates the schedule with the message GRPs recommend significantly more vehicle purchases than do those solutions from a model that evaluates the schedule with the vehicle GRPs. However, these results are misleading in that the numbers of optimum solutions analyzed between the two treatments are different. In fact, while a total of 120 largest message GRP producing schedules have been obtained for the present analyses, only 60 schedules producing the largest GRPs have been inputted for the analyses. The number of the message GRP producing schedules is larger than that of the vehicle GRP producing schedule is because the present study also questions whether the various sizes of message weights would affect the selection of vehicles. To test the impact of the size of message weights on vehicle selection, which will be presented in the next section, the present study has obtained the message GRP producing schedules with the two different levels of message weights (i.e., .6 and .4). To compare the vehicle selections of the message GRP schedules with those of the vehicle GRP schedules shown in Table 19 and Table 20, it is necessary to divide the raw frequency numbers in the table of the message GRP schedules by two. After the adjustment, the total number of insertions recommended between the two schedules has become almost even. In other words, these 120 maximum message GRP schedules have recommended a total of 1,453 insertions while the 60 largest vehicle GRP producing schedules have recommended a total of 721 insertions at the high budget levels (Table 19). Chi-square statistics also support that this difference in the total number of vehicle selections is not statistically significant. In addition, a comparison of the difference in the allocation of the insertions through the time period shows that both the maximum vehicle GRP

Table 20
Statistical Comparison of the Vehicle Selection for the Largest Message GRP Producing Schedules Vs. the Vehicle Selection for the Largest Vehicle GRP Producing Schedules at the Low Budget Levels

Vehicle Selection for the Largest Message GRP Producing Schedules [a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	36 (3.3[c])	23 (2.1)	17 (1.6)	16 (1.5)	4 (0.4)	2 (0.2)	98 (9.0)
Magazine 2	224 (20.6)	210 (19.3)	206 (18.9)	169 (15.5)	111 (10.2)	70 (6.4)	990 (91.0)
Total	260 (23.9)	233 (21.4)	223 (20.5)	185 (17.0)	115 (10.6)	72 (6.6)	1088[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 120 largest message GRP producing schedules. "Largest Message GRP Producing Schedules" mean that the gross rating points which is the benchmark for selecting an optimum solution was adjusted to reflect the advertising copy effect once the vehicle ratings were applied.

[b] 1,088 represents a total number of magazines recommended from the total of 120 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 120 optimum solutions in total recommends 3.3% of a total 1,088 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Largest Vehicle GRP Producing Schedules[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	23 (4.3)	11 (2.1)	5 (0.9)	2 (0.4)	4 (0.8)	0 (0.0)	45 (8.4)
Magazine 2	116 (21.7)	108 (20.2)	92 (17.2)	75 (14.0)	61 (11.4)	38 (7.1)	490 (91.6)
Total	116 (26.0)	119 (22.3)	97 (18.1)	77 (14.4)	65 (12.2)	38 (7.1)	535 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 largest vehicle GRP producing schedules. "Largest Vehicle GRP Producing Schedules" mean that the gross rating points which is the benchmark for selecting an optimum solution was not adjusted to reflected the advertising copy effect once the vehicle ratings were applied.

Chi-Square Test Results for the Largest Message GRP Producing Schedules Vs. the Largest Vehicle GRP Producing Schedules at Low Budget Levels

Use of Message Effect	Degrees of Freedom	Value (χ^2)*
Total Number of Vehicle Insertions	1	0.15
Monthly Advertising Allocation of Optimum Schedules	5	6.38
Vehicle Preference of Optimum Schedules	1	0.24

* None of the tested variable were significant at the .20 levels.

schedules and the largest message GRP producing schedules have suggested heavy advertising in the earlier campaign period. The difference in the allocation of the insertions through the time period between the schedules has not been found in Chi-square test. On the other hand, the comparison of the difference in the selection of the magazines indicates that the schedules producing the largest vehicle GRPs have suggested a lower CPM magazine (i.e., Magazine 2) more frequently than do the maximum message GRP schedules (89.5 percent vs. 87.4 percent). This difference is statistically significant at the .10 level. As stated, any single significant difference among these three tests can provide enough empirical support to declare that the two solutions are different in the vehicle selection. In summary, the vehicle and insertion selections of the largest message GRP producing schedules are different from the selections of the schedules producing the largest vehicle GRPs <u>at the high budget levels</u>.

<u>At the low budget levels</u>, the 120 maximum message GRP schedules have recommended a total of 1,088 insertions while the 60 schedules producing the optimum vehicle GRPs have recommended a total of 535 insertions (Table 20). Considering the number of optimum solutions analyzed for the present study, these numbers are comparable. In addition, a comparison of the difference in the allocation of the insertions through the time period shows that both the optimum vehicle GRP schedules and the optimum message GRP schedules have suggested heavy advertising in the earlier campaign period. Also, the comparison of the largest vehicle GRP producing schedules with the largest vehicle GRP producing schedules in the selection of the magazines indicates that the percentages of the lower CPM magazine recommended in the optimum schedules are nearly identical (91 percent vs. 91.6 percent). In fact, Chi-square statistics indicate that there is no difference in any of the above comparisons

between the two treatments found at the low budget levels. In summary, while evaluating a schedule with message GRPs has an impact on the vehicle selection of the optimum schedule at the high budget levels, there is no difference in vehicle selections between the optimum message GRP schedules and the optimum vehicle GRP schedules at the low budget levels.

Degree of Message Weights

As stated, in a situation where the size of the message weights can only be determined depending on the specific creative factors such as emotional appeal, message complexity, or the quality of the message, the knowledge of how the different sizes of message weights will influence the selection of the optimum schedules will also be helpful in determining the nature of the media selection process. A significant impact of this independent variable (i.e., size of the message weights) could force the planner not only to estimate the media impact in terms of message figures but also to have a correct estimation of the message weights (i.e., the percentage of people who are exposed to the advertisement out of the number of people who are exposed to the magazine).

Table 21 represents the results of the statistical comparison of the vehicle selection for the optimum schedules with high message weight (= .6) vs. the vehicle selection for the optimum schedules with low message weight (= .4) at the high budget levels. The results indicate that there is no difference between the total number of vehicle insertions selected in the 60 optimum solutions from a model with high message weights and the that number in the 60 optimum solutions from a model with low message weights (729 vs. 721). In addition, the analysis of these 60 optimum

Table 21
Statistical Comparison of the Vehicle Selection for the Optimum Schedules with High Message Weight Vs. the Vehicle Selection for the Optimum Schedules with Low Message Weight at the High Budget Levels

Vehicle Selection for the Optimum Schedules with High Message Weight [a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	29 (4.0[c])	18 (2.5)	17 (2.3)	11 (1.5)	11 (1.5)	8 (1.1)	94 (12.9)
Magazine 2	120 (16.5)	115 (15.8)	116 (15.9)	108 (14.8)	99 (13.6)	77 (10.6)	635 (87.1)
Total	297 (20.4)	260 (18.2)	261 (18.2)	241 (16.3)	230 (15.1)	164 (11.7)	729[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with High message weight. "Optimum schedules with high message weight" mean that the largest GRP producing schedules were determined based on GRPs which has been adjusted with high message weight (=0.6).

[b] 729 represents a total number of magazines recommended from the total of 60 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 60 optimum solutions in total recommends 4.0% of a total 729 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules with Low Message Weight [d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	33 (4.6)	18 (2.5)	15 (2.1)	11 (1.5)	11 (1.5)	1 (0.1)	89 (12.3)
Magazine 2	115 (15.9)	109 (15.1)	113 (15.6)	111 (15.3)	109 (15.1)	78 (10.8)	635 (87.7)
Total	148 (20.4)	129 (17.5)	128 (17.7)	122 (16.9)	120 (16.6)	79 (10.9)	721 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with Low message weight. "Optimum schedules with low message weight" mean that the largest GRP producing schedules were determined based on GRPs which has been adjusted with low message weight (=0.4).

Chi-Square Test Results for the Optimum Schedules with High Message Weight Vs. the Optimum Schedules with Low Message Weight at High Budget Levels

Degree of Message Weights	Degrees of Freedom	Value (χ^2)*
Total Number of Vehicle Insertions	1	0.04
Monthly Advertising Allocation of Optimum Schedules	5	0.91
Vehicle Preference of Optimum Schedules	1	0.12

* None of the tested variables were significant at the .20 levels.

solutions at each group shows that the vehicle selection of the optimum schedules from a model with high message weight and the vehicle selection of the optimum schedules from a model with low message weight are similar in the contrast of the differences in the choice of the two magazines in the optimum schedules (87.1 percent for low CPM vehicle in a model with high message weights vs. 87.7 percent in a model with low message weights) and in the contrast of the difference in the advertising allocation through time. The results of Chi-square statistics show that the study has found no significant differences in any of the three tests at the high budget levels (Table 21).

At the low budget levels, the results are quite consistent with those at the high budget levels (Table 22). The total number of vehicle insertions selected in the 60 largest GRP producing schedules in each group was similar (528 vs. 560), and the model recommends heavy advertising in the lower CPM magazine (i.e., Magazine 2) despite the size of the message weight used. Finally, the ratio of advertising allocation through a six-month period between the schedules with a high message weight group and those with a low message weight group was similar. These findings also have been supported in Chi-square tests. In summary, despite the size of the message weights, the model seems to suggest quite similar vehicle selections at both budget levels. In other words, a successful creative campaign which will have high message weight will affect the overall effectiveness of the advertising campaign, but will not affect the structure of the media schedule.

Media Quantity Discounts

To see if the model's consideration of the media quantity discounts in the calculation of the schedule cost can make a difference in the selection of vehicles and

Table 22
Statistical Comparison of the Vehicle Selection for the Optimum Schedules with High Message Weight Vs. the Vehicle Selection for the Optimum Schedules with Low Message Weight at the Low Budget Levels

Vehicle Selection for the Optimum Schedules with High Message Weight [a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	14 (2.7[c])	8 (1.5)	11 (2.1)	9 (1.7)	1 (0.2)	0 (0.0)	43 (8.1)
Magazine 2	110 (20.8)	107 (20.3)	106 (20.1)	86 (16.3)	48 (9.1)	28 (5.3)	485 (91.9)
Total	124 (23.5)	115 (21.8)	117 (22.2)	95 (18.0)	49 (9.3)	28 (5.3)	528[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with High message weight. "Optimum schedules with high message weight" mean that the largest GRP producing schedules were determined based on GRPs which has been adjusted with high message weight (=0.6).

[b] 528 represents a total number of magazines recommended from the total of 60 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 60 optimum solutions in total recommends 2.7% of a total 528 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules with Low Message Weight [d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	22 (3.9)	15 (2.7)	6 (1.1)	7 (1.3)	3 (0.5)	2 (0.4)	55 (9.8)
Magazine 2	114 (20.4)	103 (18.4)	100 (17.9)	83 (14.8)	63 (11.3)	42 (7.5)	505 (90.2)
Total	136 (24.3)	118 (21.1)	106 (18.9)	90 (16.1)	66 (11.8)	44 (7.9)	560 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with Low message weight. "Optimum schedules with low message weight" mean that the largest GRP producing schedules were determined based on GRPs which has been adjusted with low message weight (=0.4).

Chi-Square Test Results for the Optimum Schedules with High Message Weight Vs. the Optimum Schedules with Low Message Weight at Low Budget Levels

Degree of Message Weights	Degrees of Freedom	Value (χ^2)*
Total Number of Vehicle Insertions	1	0.94
Monthly Advertising Allocation of Optimum Schedules	5	6.40
Vehicle Preference of Optimum Schedules	1	0.93

* None of the tested variables were significant at the .20 levels

their insertions in the optimum schedules, the frequency of the vehicle insertions and its percentage to the total vehicle insertions recommended in the maximum GRP schedules have been analyzed. To illustrate, a total of 90 optimum schedules, generated from a model which calculated the media schedule cost considering media quantity discounts, have been compared to those of the 90 optimum schedules from a model without a media quantity discount option at each budget level. Table 23 and Table 24 show the results of the statistical comparison of the vehicle selection for the optimum schedules both from a model with media quantity discounts and from a model without a media quantity discount.

At the high budget levels, the results indicate that the largest GRP producing schedules obtained with the consideration of media quantity discounts in calculating the schedule cost of each option are quite different from the solutions obtained without the consideration of the media discounts in terms of the total number of vehicle insertions selected and in terms of the choice of the magazines in the optimum schedules. Table 23 indicates that the 90 optimum schedules obtained from a model with this independent variable (i.e., media quantity discounts) recommended a total of 1,128 insertions, while the 90 optimum schedules obtained from a model without this variable recommended a total of 1,046 insertions. This comparison illustrates that a model was able to recommend nearly one more insertion per optimum schedule simply by considering the media quantity discounts in calculation of the schedule cost, even with a small data base, at the high budget levels. This difference was statistically significant at the .10 level . In addition, the model with media quantity discounts variable suggested lower CPM magazine (i.e., Magazine 2) less frequently than did the model without this variable (87.2 percent vs. 89 percent). This difference was statistically significant at the .20 level .

Table 23
Statistical Comparison of the Vehicle Selection for the Optimum Schedules from a Model with Media Quantity Discount Option Vs. the Vehicle Selection For the Optimum Schedules from a Model without Media Quantity Discount Option at the High Budget Levels

Vehicle Selection for the Optimum Schedules from a Model with Media Quantity Discount Option[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	52 (4.6[c])	30 (2.7)	22 (2.0)	15 (1.3)	16 (1.4)	9 (0.8)	144 (12.8)
Magazine 2	177 (15.7)	175 (15.5)	173 (15.3)	170 (15.1)	158 (14.0)	131 (11.6)	984 (87.2)
Total	229 (20.3)	205 (18.2)	195 (17.3)	185 (16.4)	174 (15.4)	140 (12.4)	1128[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 90 optimum schedules from a model with media quantity discount option. "Optimum schedules from a model with media quantity discount option" mean that the largest GRP producing schedules have been determined from a model that applies media quantity discounts in calculating the total cost of each alternative schedule.

[b] 1128 represents a total number of magazines recommended from the total of 90 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 90 optimum solutions in total recommends 4.6% of a total 1128 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules from a Model without Media Quantity Discount Option[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	40 (3.8)	20 (1.9)	21 (2.0)	15 (1.4)	15 (1.4)	4 (0.4)	115 (11.0)
Magazine 2	175 (16.7)	164 (15.7)	169 (16.2)	161 (15.4)	154 (14.7)	108 (10.3)	931 (89.0)
Total	215 (20.6)	184 (17.6)	190 (18.2)	176 (16.8)	169 (16.2)	112 (10.7)	1046 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 90 optimum schedules from a model without media quantity discount option. "Optimum schedules from a model without media quantity discount option" mean that the largest GRP producing schedules have been determined from a model that calculates the total cost of each alternative schedule with fixed magazine costs.

Chi-Square Test Results for the Optimum Schedules from a Model with Media Discount Vs. the Optimum Schedules from a Model without Media Discount at High Budget Levels

Media Quantity Discounts	Degrees of Freedom	Value (χ^2)
Total Number of Vehicle Insertions	1	3.09*
Monthly Advertising Allocation of Optimum Schedules	5	1.96
Vehicle Preference of Optimum Schedules	1	1.62**

* Significant at the .10 levels
** Significant at the .20 levels
*** The other variable was not significant at the .20 levels.

Table 24
Statistical Comparison of the Vehicle Selection for the Optimum Schedules from a Model with Media Quantity Discount Option Vs. the Vehicle Selection For the Optimum Schedules from a Model without Media Quantity Discount Option at the Low Budget Levels

Vehicle Selection for the Optimum Schedules from a Model with Media Quantity Discount Option[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	32 (3.8[c])	19 (2.3)	9 (1.1)	11 (1.3)	2 (0.2)	1 (0.1)	74 (8.9)
Magazine 2	172 (20.6)	168 (20.1)	149 (17.8)	123 (14.7)	93 (11.1)	56 (6.7)	761 (91.1)
Total	204 (24.4)	187 (22.4)	158 (18.9)	134 (16.1)	95 (11.4)	57 (6.8)	835[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 90 optimum schedules from a model with media quantity discount option. "Optimum schedules from a model with media quantity discount option" mean that the largest GRP producing schedules have been determined from a model that applies media quantity discounts in calculating the total cost of each alternative schedule.

[b] 835 represents a total number of magazines recommended from the total of 90 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 90 optimum solutions in total recommends 3.8% of a total 835 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules from a Model without Media Quantity Discount Option[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	27 (3.4)	15 (1.9)	13 (1.7)	7 (0.9)	6 (0.8)	1 (0.1)	69 (8.8)
Magazine 2	168 (21.3)	150 (19.0)	149 (18.9)	121 (15.4)	79 (10.0)	52 (6.6)	719 (91.2)
Total	195 (24.8)	165 (20.9)	162 (20.6)	128 (16.3)	85 (10.8)	53 (6.7)	788 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 90 optimum schedules from a model without media quantity discount option. "Optimum schedules from a model without media quantity discount option" mean that the largest GRP producing schedules have been determined from a model that calculates the total cost of each alternative schedule with fixed magazine costs.

Chi-Square Test Results for the Optimum Schedules from a Model with Media Discount Vs. the Optimum Schedules from a Model without Media Discount at Low Budget Levels

Media Quantity Dicsounts	Degrees of Freedom	Value (χ^2)*
Total Number of Vehicle Insertions	1	1.36
Monthly Advertising Allocation of Optimum Schedules	5	1.10
Vehicle Preference of Optimum Schedules	1	0.01

* None of the tested variables were significant at the .20 levels.

At the low budget levels, however, the maximum GRP schedules between the two treatments are quite similar in all of these three tests (Table 24). The author believes that this is mainly due to the small amount of the advertising budget. Considering the small amount of the advertising budget, the model suggests the smaller insertions so that the consideration of media discounts could not make a difference in the vehicle selections. In summary, the use of this variable has an impact on the selection of vehicles in the optimum solutions when the campaign has a high advertising budget.

Carryover Effect

Use of Carryover Effect

The final independent variable tested in the present analysis is the effect of carryover in the media selection process. As stated, carryover effect in the present study refers to the amount of advertising exposure carried over to the subsequent time period. To see if the consideration of carryover effect in the model in the estimation of GRPs has an impact on the vehicle selection of the optimum schedules, Table 25 and Table 26 have been developed.

Like the verification of the impact of message effect variable on vehicle selections and their insertions, the optimum solutions from a model with carryover effect are not equal to those from a model without carryover effect. While the number of optimum solutions from a model with carryover effect is 120, due to the verification of the various degrees of carryover weights, the number of optimum solutions from a

Table 25
Statistical Comparison of the Vehicle Selection for the Optimum Schedules from a Model with Carryover Effect Option Vs. the Vehicle Selection For the Optimum Schedules from a Model without Carryover Effect Option at the High Budget Levels

Vehicle Selection for the Optimum Schedules from a Model with Carryover Effect Option[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	64 (4.4[c])	33 (2.3)	30 (2.1)	23 (1.6)	20 (1.4)	7 (0.5)	177 (12.2)
Magazine 2	232 (16.0)	222 (15.3)	226 (15.5)	219 (15.1)	212 (14.6)	167 (11.5)	1278 (87.8)
Total	296 (20.3)	255 (17.5)	256 (17.6)	242 (16.6)	232 (16.0)	174 (12.0)	1455[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 120 optimum schedules from a model with carryover effect option. "Optimum schedules from a model with carryover effect option" mean that the largest GRP producing schedules have been determined based on GRPs which accommodate the effect of current advertising and the effect of advertising in the past months.

[b] 1455 represents a total number of magazines recommended from the total of 120 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 120 optimum solutions in total recommends 4.4% of a total 1455 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules from a Model without Carryover Effect Option[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	28 (3.9)	17 (2.4)	13 (1.8)	7 (1.0)	11 (1.5)	6 (0.8)	82 (11.4)
Magazine 2	120 (16.7)	117 (16.3)	116 (16.1)	112 (15.6)	100 (13.9)	72 (10.0)	637 (88.6)
Total	148 (20.6)	134 (18.6)	129 (17.9)	119 (16.6)	111 (15.4)	78 (10.9)	719 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 optimum schedules from a model without carryover effect option. "Optimum schedules from a model without carryover effect option" mean that the largest GRP producing schedules have been determined based on GRPs which only accommodate the effect of current advertising.

Chi-Square Test Results for the Optimum Schedules from a Model with Carryover Effect Vs. the Optimum Schedules from a Model without Carryover Effect at High Budget Levels

Use of Carryover Effect	Degrees of Freedom	Value (χ^2)*
Total Number of Vehicle Insertions	1	0.10
Monthly Advertising Allocation of Optimum Schedules	5	3.05
Vehicle Preference of Optimum Schedules	1	0.20

* None of the tested variables were significant at the .20 levels.

Table 26
Statistical Comparison of the Vehicle Selection for the Optimum Schedules from a Model with Carryover Effect Option Vs. the Vehicle Selection For the Optimum Schedules from a Model without Carryover Effect Option at the Low Budget Levels

Vehicle Selection for the Optimum Schedules from a Model with Carryover Effect Option[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	35 (3.2[c])	19 (1.7)	14 (1.3)	11 (1.0)	5 (0.5)	1 (0.1)	85 (7.8)
Magazine 2	226 (20.7)	209 (19.1)	200 (18.3)	168 (15.4)	123 (11.2)	83 (7.6)	1009 (92.2)
Total	261 (23.9)	228 (20.8)	214 (19.6)	179 (16.4)	128 (11.7)	84 (7.7)	1094[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 120 optimum schedules from a model with carryover effect option. "Optimum schedules from a model with carryover effect option" mean that the largest GRP producing schedule have been determined based on GRPs which accommodate the effect of current advertising and the effect of advertising in the past months.

[b] 1094 represents a total number of magazines recommended from the total of 120 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 120 optimum solutions in total recommends 3.2% of a total 1094 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules from a Model without Carryover Effect Option[d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	24 (4.5)	15 (2.8)	8 (1.5)	7 (1.3)	3 (0.6)	1 (0.2)	58 (11.0)
Magazine 2	114 (21.6)	109 (20.6)	98 (18.5)	76 (14.4)	49 (9.3)	25 (4.7)	471 (89.0)
Total	138 (26.1)	124 (23.4)	106 (20.0)	83 (15.7)	52 (9.8)	26 (4.9)	529 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 optimum schedules from a model without carryover effect option. "Optimum schedules from a model without carryover effect option" mean that the largest GRP producing schedule have been determined based on GRPs which only accommodate the effect of current advertising.

Chi-Square Test Results for the Optimum Schedules from a Model with Carryover Effect Vs. the Optimum Schedules from a Model without Carryover Effect at Low Budget Levels

Use of Carryover Effect	Degrees of Freedom	Value (χ^2)
Total Number of Vehicle Insertions	1	0.60
Monthly Advertising Allocation of Optimum Schedules	5	13.51*
Vehicle Preference of Optimum Schedules	1	6.05*

* Significant at the .05 levels

** Other variables were not significant at the .20 levels.

model without carryover effect is 60 (Table 13 and Table 14). To compare the total number of vehicle insertions recommended between the two models (i.e. the model with carryover effect and the model without carryover effect), it is necessary to divide the vehicle insertions at the table of the vehicle selection for the optimum schedules with carryover effect by two.

As Table 25 represents, the two models recommend almost the same numbers of total insertions at the high budget levels when the number of total insertions from a model with carryover effect has been adjusted (727.5 vs. 719). In addition, the largest GRP producing schedules generated from a model which incorporates the carryover effect are not different from those from a model which does not incorporate carryover effect in terms of the choice of the magazines and the advertising allocation through months. Chi-square tests indicate that none of the three tests conducted in the present analyses (i.e., a test of the difference in total number of vehicle insertions selected, a test of the difference in the selection of the magazines, and a test of the difference in the allocation of the insertions through the time period) produced a significant difference.

The findings on the verification of impact of the use of carryover effect on the vehicle selections and their insertions at the low budget levels is somewhat different from those findings at the high budget levels (Table 26). Although the solutions from the two models recommend a similar number of vehicle purchases after the number in the solutions from a model with carryover effect has been adjusted (547 vs. 529), the model that incorporates the carryover effect recommended a lower CPM magazine more frequently in the recommended schedules than did the model that does not incorporate the carryover effect (92.2 percent vs. 89.0 percent). In addition, when the percentage figures in the column total cells between the two tables are compared, the model that does not consider carryover effect suggests more advertising in the earlier months than

does the model with carryover effect at the low budget levels. These two results are significant at the .05 level . (Table 26). In summary, while carryover effect has no impact on the vehicle selection at the high budget levels, it does have an effect on the vehicle selection at the low budget levels.

Degree of Carryover Weights

As explained, the review of literature has shown that the size of the carryover effect on advertising exposure varies depending on factors such as meaningfulness of the stimuli, similarity of items, the size of the advertising message, and the levels of original learning. The present study has tested two different levels of carryover rates in this verification process to see if the size of the carryover weights can affect the media selection process. Earlier, this study has reported the results of the impact of the size of the carryover effect on adjusted gross rating points (AGRPs). The author has found that the various size of carryover weights does not affect the value of AGRPs. This section reports the results of the effect of this independent variable (i.e., size of carryover effect) on the selection of vehicle. If the results support the findings from the effect of this variable on AGRPs, the present study will claim with confidence that the size of carryover weights has no impact in the media selection process so that the model can neglect such a variable in obtaining the largest GRP producing schedule. Table 27 and Table 28 report the findings of the impact of this variable on the selection of vehicles and their insertions.

At the high budget levels, the 60 optimum schedules obtained from a model with high carryover weight (=.55) have recommended a total of 730 insertions, while

Table 27
Statistical Comparison of the Vehicle Selection for the Optimum Schedules with High Carryover Weight Vs. the Vehicle Selection for the Optimum Schedules with Low Carryover Weight at the High Budget Levels

Vehicle Selection for the Optimum Schedules with High Carryover Weight [a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	34 (4.7[c])	17 (2.3)	17 (2.3)	13 (1.8)	13 (1.8)	4 (0.6)	98 (13.4)
Magazine 2	114 (15.6)	109 (14.9)	117 (16.0)	111 (15.2)	100 (13.7)	81 (11.1)	632 (86.6)
Total	148 (20.3)	126 (17.3)	134 (18.4)	124 (17.0)	113 (15.5)	85 (11.6)	730[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with High carryover weight. "Optimum schedules with high carryover weight" mean that the largest GRP producing schedule have been determined based on GRPs which accommodate the effect of current advertising and the higher rate (=.55) of advertising carryover effect in the past months.

[b] 730 represents a total number of magazines recommended from the total of 60 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 60 optimum solutions in total recommends 4.7% of a total 730 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules with Low Carryover Weight [d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	30 (4.1)	16 (2.2)	13 (1.8)	10 (1.4)	7 (1.0)	3 (0.4)	79 (10.9)
Magazine 2	118 (16.3)	113 (15.6)	109 (15.0)	108 (14.9)	112 (15.5)	86 (11.9)	646 (89.1)
Total	148 (20.4)	129 (17.8)	122 (16.8)	118 (16.3)	119 (16.4)	89 (12.3)	725 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with Low carryover weight. "Optimum schedules with low carryover weight" mean that the largest GRP producing schedule have been determined based on GRPs which accommodate the effect of current advertising and the lower rate (=.35) of advertising carryover effect in the past months.

Chi-Square Test Results for the Optimum Schedules with High Carryover Effect Vs. the Optimum Schedules with Low Carryover Effect at High Budget Levels

Degree of Carryover Weights	Degrees of Freedom	Value (χ^2)
Total Number of Vehicle Insertions	1	0.02
Monthly Advertising Allocation of Optimum Schedules	5	0.98
Vehicle Preference of Optimum Schedules	1	2.18*

* Significant at the .20 levels
** Other variables were not significant at the .20 levels.

Table 28
Statistical Comparison of the Vehicle Selection for the Optimum Schedules with High Carryover Weight Vs. the Vehicle Selection for the Optimum Schedules with Low Carryover Weight at the Low Budget Levels

Vehicle Selection for the Optimum Schedules with High Carryover Weight [a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	21 (3.8[c])	9 (1.6)	7 (1.3)	5 (0.9)	2 (0.4)	1 (0.2)	45 (8.2)
Magazine 2	114 (20.7)	104 (18.8)	104 (18.8)	81 (14.7)	59 (10.7)	45 (8.2)	507 (91.9)
Total	135 (24.5)	113 (20.5)	111 (20.1)	86 (15.6)	61 (11.1)	46 (8.3)	552[b] (100.0)

[a] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with High carryover weight. "Optimum schedules with high carryover weight" mean that the largest GRP producing schedule have been determined based on GRPs which accommodate the effect of current advertising and the higher rate (=.55) of advertising carryover effect in the past months.

[b] 552 represents a total number of magazines recommended from the total of 60 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 60 optimum solutions in total recommends 3.8% of a total 552 insertions for Magazine 1 (i.e. high CPM magazine) in Month 1.

Vehicle Selection for the Optimum Schedules with Low Carryover Weight [d]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	14 (2.6)	10 (1.9)	7 (1.3)	6 (1.1)	3 (0.6)	0 (0.0)	40 (7.4)
Magazine 2	112 (20.7)	105 (19.4)	96 (17.7)	87 (16.1)	64 (11.8)	38 (7.0)	502 (92.6)
Total	126 (23.3)	115 (21.2)	103 (19.0)	93 (17.2)	67 (12.4)	38 (7.0)	542 (100.0)

[d] The table reflects the aggregate of the magazines recommended for 60 optimum schedules with Low carryover weight. "Optimum schedules with low carryover weight" mean that the largest GRP producing schedule have been determined based on GRPs which accommodate the effect of current advertising and the lower rate (=.35) of advertising carryover effect in the past months.

Chi-Square Test Results for the Optimum Schedules with High Carryover Effect Vs. the Optimum Schedules with Low Carryover Effect at Low Budget Levels

Degree of Carryover Effect	Degrees of Freedom	Value (χ^2)*
Total Number of Vehicle Insertions	1	0.09
Monthly Advertising Allocation of Optimum Schedules	5	1.85
Vehicle Preference of Optimum Schedules	1	0.23

* None of the tested variables were significant at the .20 levels.

the 60 schedules obtained from a model with low carryover weight (=.35) have recommended a total of 725 insertions as Table 27 indicates. In addition, the analysis of these 60 optimum solutions at each group shows that the vehicle selection of the optimum schedules from a model with high message weight and that of the optimum schedules from a model with low message weight are similar when the comparison of the difference in the advertising allocation through time is applied. The results of Chi-square statistics show no significant differences between these two tests at the high budget levels (Table 27). However, in the test of the choice of the two magazines in the optimum schedules, the model with low carryover weight recommended the lower CPM magazine more often than did the model with high carryover weight (86.6 for low CPM vehicle in a model with high carryover weights vs. 89.1 percent in a model with low message weights). This difference was significant at the .20 level .

At the low budget levels, the present study has found no significant difference in any of these three tests (Table 28). The total number of vehicle insertions selected in the 60 largest GRP producing schedules in each group was similar (552 vs. 542), and the model recommends heavy advertising in the lower CPM magazine (i.e., Magazine 2) despite the size of the carryover weight used. Finally, the ratio of advertising allocation through a six-month period between the schedules with a high carryover weight group and those with a low carryover weight group was similar. In summary, despite the size of the message weights, the model suggests quite similar vehicle selections when a model handles the small amount of advertising. However, the model seems to suggest the lower CPM magazine more frequently with low carryover weight at the high advertising budget levels.

Summary

The test of the impact of any element on vehicle selections and their insertions determines if the use of any element in the model makes the optimum schedules different. This test has been conducted by comparing the frequency of vehicle insertions between the two treatment groups. To determine the significance of the difference, Chi-square statistics have been applied. This chapter has reported the complete results of the test of each element on vehicle selections and their insertions.

The results indicate that the model suggests a quite different optimum schedule when the timing of advertising variable was examined in the model at both budget levels. In addition, the maximum GRP schedules become different at the high budget level with the use of message effect, the use of media discounts, and the size of carryover weights. The study has also found a difference in vehicle selections at the low budget level when the model examines the carryover effect. However, these results can be considered partial findings of the verification of the model. Even if the model suggests the different schedules with the use of an element, such an element cannot be significant in the model unless the difference in vehicle selection leads to the difference in media impact. To illustrate, an element cannot be significant if the two optimum schedules have almost the same GRPs, despite the fact that the two schedules are not identical. The previous chapter has reported whether the difference in vehicle selections has led to the difference in media impact. The conclusions of the impact of every element in the model will be made in the next chapter.

CHAPTER 8
RESULTS: TESTS OF HYPOTHESES

Introduction

To verify the proposed media selection model, the present study has tested the impact of the four independent variables on the media selection process. These four variables, which are the major elements in the proposed model, include the timing of advertising, message effect, media quantity discounts, and carryover effect. In verifying the message effect variable and carryover effect variable, the present study not only has tested whether the accommodation of these variables in the model has any impact on the media selection process, but also has tested whether the size of the message and carryover weight has any impact, since the size of these weights can only be determined based on specific advertising situations. In Chapter 5, the author has set a series of hypotheses to test an impact of each independent variable on the media selection process. So far, the current study has reported all the empirical findings necessary for testing hypotheses. In this section, this study will summarize the results reported in the previous section, will make a decision of whether Hypothesis should be rejected or not, and will give an implication of each decision. For a better understanding of the results of the verification of the model, Table 29 summarizes the results of the test of the significance of the independent variables.

Table 29
Summary of the Test of the Significance of the Independent Variables on the Media Selection Process

Independent Variable		Budget Levels	Findings of the Independent Effects of Variables: Significant Impact on AGRPs	Significant Impact on Vehicle Selection
Timing of Advertising		High	Yes*	Yes
		Low	Yes	Yes
Message Effects	Use of Message effect	High	Yes	Yes
		Low		
	Size of Message weights	High	Yes	
		Low		
Media Quantity Discounts		High	Yes	Yes
		Low	Yes	
Carryover Effects	Use of Carryover effect	High		
		Low		Yes
	Size of Carryover weights	High		Yes
		Low		

* "Yes" indicates that the accommodation of the independent variable in the model has made an impact on the size of Adjusted GRPs (AGRPs).

Timing of Advertising

In a situation where the typical length of a media plan is three months to one year, it is important to know if the consideration of the timing of advertising variable in the model is important to increase the gross rating points (GRPs), which is the objective function of the model. Incorporating the timing of advertising into the model forces the model to evaluate the schedules in which vehicles are alternated through months. The model that incorporates the timing of advertising variable has been termed the "long-term optimization model." As stated, the verification of effect of each independent variable in the media selection process requires two tests: the verification of the impact on the objective function and the verification of the impact on the vehicle selection. Based on the results found in these two tests of each variable, the present study will be able to determine the effect of each variable in the media selection process.

For the test of the impact of the timing of advertising variable on Adjusted GRPs (AGRPs), Hypothesis 1 has been developed. Hypothesis 1 poses that there will be no difference in the estimated impact between the solutions from the long-term optimization model and the solutions that a monthly optimization schedule is duplicated month after month, if all other factors are held constant for high and low budget levels. Table 5 and Table 6 (p. 125) have shown the results of the effect of this independent variable on AGRPs. The results indicate that the optimum schedules recommended from the long-term optimization model generates the average of 42.1 AGRPs higher than the schedule from the duplicated monthly optimization model at the high budget levels. At the low budget levels, the optimum schedule from the long-term optimization model generates about 32 AGRPs higher than the schedule from the duplicated monthly optimization model. Since these differences were statistically significant at the .01 level, the author rejects Hypothesis 1. However, since the decision of the effect of the

timing of advertising variable in the media selection process can only be made after the test of the impact on the vehicle selection, the implication of this rejection will be presented after the report of the test of the impact on vehicle selection.

In the moment when Hypothesis 1 has been rejected, the only caution from making the conclusion that the examination of time frame in the optimization model is essential in obtaining an optimum solution is whether the difference in the value of Adjusted GRPs (AGRPs) comes from sampling error. If it is, the solutions between the two model may have been similar. This is why Hypothesis 7 can provide supporting evidence in verifying the impact of an element in the media selection process. Hypothesis 7 argues that there will be no difference in the selection of the vehicles and their insertions between the results of the long-term optimization model and the results that a monthly optimization schedule is duplicated month after month if all other factors are held constant for high and low budget levels. Earlier, this study has reported that the optimum schedules from a long-term optimization model were quite different from the schedules from the model that does not incorporate the timing of advertising variable at both budget levels (Table 17, p. 147, and Table 18, p. 151). Therefore, Hypothesis 7 has also been rejected. In fact, the solutions from the long-term optimization model recommend the average of two more vehicle purchases than those from the monthly optimization model do. In addition, the long-term optimization model recommended heavier advertising in the earlier time periods and recommended more purchase of the lower CPM magazine.

In summary, the additional evaluation of the options in which vehicles are alternated through months allows the model to choose a schedule with more insertions and the increased vehicle insertions reflect more gross rating points (GRPs) in the

schedule. Therefore, the present study concludes that the timing of advertising variable plays an essential role in the media selection process.

This conclusion could be important to both model builders and model users. To model builders, the present study has shown that the media selection model should not only evaluate the schedules in which single month schedule is duplicated but also evaluate the schedules in which vehicles are alternated to obtain the validity of the recommended optimum schedule. In Table 5 and Table 6, this study has shown that the schedule from the model which does not consider this variable generates about 40 percent less gross rating points (GRPs) than the schedule from the long-term optimization model does. The amount of the difference in the Adjusted GRPs (AGRPs) between the two schedules could be somewhat overestimated considering the fact that this study used a rather small data base. However, the author believes the amount of difference in GRPs between the two models, even with a more comprehensive data base, should be significant. Anyway, this finding shows that the model which produces a single month optimization schedule may not be useful in the long-term media planning.

The results imply that model users should be very careful in selecting the vehicle for the long-term media schedule. They indicate that planners may develop a long-term schedule in which estimated media impact is far below the media impact of a true optimum schedule if they use the monthly optimization model. The use of subjective reasoning in the allocation of advertising budget through months may be even more dangerous. Considering the fact that the average advertising budget for 720 optimization analyses conducted for this study was \$712,500, the 40 percent less gross rating points (GRPs) in the schedule from a model without this variable would mean the loss of \$285,000. Once again, this value may over-estimate the loss of impact in

the real media planning, but it certainly shows the significance of this variable in the media selection model. The planners should certainly be careful in the decision of the timing of advertising.

Message Effect

Use of Message Effects

In a situation where most syndicated data services provide vehicle ratings rather than message ratings and where most reach/frequency models which estimate media impact produce the vehicle exposure distribution, the subject of message effect in media planning has been a challenging issue for several decades. While most media researchers acknowledge the importance of this issue, it is also true that media planners have ignored such differences. In fact, about two thirds of advertising agencies still estimate the impact of the schedule based on vehicle exposure (Kreshel et al., 1985; and Lancaster et al., 1986). In addition, many past media selection models estimate the media impact of the vehicle rather than the impact of the advertisement (Table 2, pp. 31-32). By testing an impact of message effect on the media selection process, the author wishes to find if such complexity of incorporating a message dimension is necessary in the optimization process. While Hypothesis 2 tests the impact of the message effect variable on Adjusted GRPs (AGRPs), Hypothesis 8 has been developed to test the impact of message effect on vehicle selection.

Hypothesis 2 states that there will be no difference between the estimated value of AGRPs from the model that determines the optimum schedule based on vehicle gross rating points and the one from the model that determines the optimum schedule

based on message gross rating points, if all other factors are held constant for high and low budget levels. Hypothesis 8 also tests the impact of the use of message weights arguing that there will be no difference in the selection of the vehicles and their insertions between the results from the model without the message effect option and those from the model with the message effect, if all other factors are held constant for high and low budget levels.

The results for the test of the impact of the message effect variable on the Adjusted GRPs (AGRPs) has been presented in Table 7 and Table 8 (p. 129). At the high budget levels, the maximum message GRP schedules had higher AGRPs than the maximum vehicle GRP schedules had. And, the amount of difference between the two treatment groups (= 18.8) was statistically significant at the .15 level. At the low budget levels, the largest message GRP producing schedules also had higher AGRPs than the schedules producing the largest vehicle GRPs had but the amount of difference between the two treatment groups (= 4.5) was not statistically significant. Since the effect of this independent variable has only been found at the high budget levels, the present study partially rejects Hypothesis 2. Although the present study has found that a model that evaluates an option with message GRPs selects the higher AGRP producing optimum schedule than the model with vehicle GRPs does, it is difficult to figure out why this is true. Due to the complicated estimation process involved in the media selection process, this study has found it difficult to know why one estimation mechanism selects a different schedule from the other. Since this question is certainly beyond the scope of the present validation, it will be left for future study.

Concerning the test of the impact of message effect on vehicle selection, the present study has found a effect of this variable at the high budget levels (Table 19, p. 152, and Table 20, p. 154). At the high budget levels, the difference in optimum

schedules between the two models mainly existed in the choice of the magazines. In other words, the model which estimates the message GRPs recommended less a lower CPM magazine than the model which estimates the vehicle GRPs. However, no difference in optimum schedules between the two models has been found at the low budget levels. Therefore, the present study partially rejects Hypothesis 8.

The results of the test of the impact on vehicle selection in this variable are consistent to those on Adjusted GRPs (AGRPs). In other words, estimating the media schedule with message GRPs is essential in the media selection process when the advertising budget is large. As Table 7 (p. 129) shows, the difference in vehicle selections between the two model could make the difference in the average of 18.8 GRPs at the high budget levels. This is the amount of error attributable to the difference only in vehicle selections. Considering the average AGRPs in the schedules from a model with vehicle GRPs is 129.9 gross rating points, this 14.5 percent difference in GRPs is considered to be fairly large. At the low budget levels, however, this variable was not sensitive enough to make any difference in the media selection process. The average high advertising budget used in this study was $839,000, while the average low advertising budget was $552,000.

One thing model users should be careful concerning this result is that the present study has been conducted with a rather small data base. In real media planning, any advertising budget would be larger than the amount of the high advertising budget used in the present study. Therefore, the author expects that the evaluation of the media schedule with message GRPs could make a significant difference in the media selection. So, unless the advertising budget is quite small, with which only one insertion per month can be purchased, the model should evaluate the schedule with message GRPs.

Degree of Message Weights

In the above section, the present study has shown that the evaluation of the media schedule with the message GRPs is important in the media selection process. This section turns attention to the question of whether the model selects the largest GRP producing schedule depending on the size of the message weight that the model applies. Message weight refers to the percentage of people who saw an advertising message out of the number of people who read the magazine. As the review of literature has found, creative factors such as ad size, the use of color, message quality, emotional appeal, or involvement influence the size of message weights. For example, the percentage of people who are likely to be exposed to a full-color advertisement will be higher than the percentage of people who are likely to be exposed to black and white advertisement if all other factors are held constant. Since the size of the message weights seems to be situation specific, the author decided to test whether the various sizes of message weights is important in the media selection process.

Hypothesis 3 poses that there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from a model that applies the low message weights and the one from a model that applies the high message weights, if all other factors are held constant for high and low budget levels. Table 9 (p. 134) shows that the model that applies higher message weights recommends an optimum schedule that has higher AGRPs than the model with lower message weights does at the high budget levels (159.7 vs. 137.8). But, there is no difference between the mean of AGRPs from the high message weights group and that from low message groups at low budget levels (Table 8, p. 129). Therefore, Hypothesis 3 has been partially rejected. As stated, AGRP is an estimated media impact with a constant message weight and

carryover weight . So, this difference is attributable to the difference in vehicle selections if the vehicle selections in optimum solutions between the model with higher message weight and the model with lower message weight are different. To make any decision of the effectiveness of this independent variable, the test of the impact on vehicle selection should be conducted.

Hypothesis 9 advances that there will be no difference in the selection of the vehicles and their insertions between the results with the low message weights and results with high message weights, if all other factors are held constant for high and low budget levels. The results of the comparison of the vehicle selections between the two models have been presented in Table 21 (p. 157) and Table 22 (p.159). The present study has shown that the vehicle selections in the optimum solutions from a model with high message weight were not different from those from a model with low message weight. Therefore, the present study accepts Hypothesis 9. In the above section, the author has argued that the difference in Adjusted GRPs (AGRPs) is attributable to the difference in vehicle selections if the vehicle selections in optimum solutions between the model with higher message weight and the model with lower message weight are different. But, the present study has found the significant difference in the test of the impact on AGRPs and no difference in the test of the impact on vehicle selection at the high budget levels. In other words, while the vehicle selections between the two models were not different, AGRPs between the two models were different. Certainly, these two findings are contradictory because AGRPs should be the same if the vehicle selections in the maximum GRP schedules between the two groups are the same. The author believes that this contradiction is due to the sampling error. This study has used a total of 720 randomly selected pairs of magazines to form the data base. So, there may be a difference in the quality of the sample in each

treatment group and that made the difference in AGRPs between the two groups in this variable. Therefore, the author decided to ignore the difference in AGRPs at the high budget levels, and concludes that the size of the message weight is not essential in the optimization process.

Earlier, this study found that the evaluation of the media schedule with the message GRPs is important in the media selection process. Yet, this section reports that the size of the message weight is not significant in the media selection process. In a situation where model users are recommended to use message weight, what can the insignificance of the size of the message weight mean? The author believes that the test of the size of the message weight concerns how accurate the message weight should be. The main reason why media planners and media selection model builders have estimated the media plan in terms of vehicle effect is because they were unable to use accurate message weights. However, the empirical findings show that most media planners have typical message weights (Kreshel et al., 1985; and Lancaster et al., 1986). Lancaster et al (1986) has found that typical message weight for consumer magazines was 52.5 percent. Although the size of the message weight varies depending on a specific advertising situation, the author believes that the size of the message weight for consumer magazines would not be far from 52.5 percent in any situation. The present findings of non-significance of the size of the message weight in the media selection process means that a minor difference in message weights does not affect the selection of the vehicle. So, it is not necessary to have an accurate measure of the message weight as long as the size of the message weight is reasonable. In a situation where it is so difficult to have an accurate message weight, this finding can be beneficial to model users.

Media Quantity Discounts

To verify the impact of media quantity discounts in the media selection process, Hypothesis 4 and Hypothesis 10 have been developed and tested. Hypothesis 4 states that there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from the model that calculates the scheduling cost considering the media quantity discounts and the one from the model which calculates the cost without considering the media quantity discounts, if all other factors are held constant for high and low budget levels. In addition, to test an impact of the use of media quantity discounts on vehicle selections, Hypothesis 10 poses that there will be no difference in the selection of the vehicles and their insertions between the results from the model that applies the media quantity discounts and those from the model which does not, if all other factors are held constant for high and low budget levels. The importance of accommodating the media quantity discounts into the media selection model has been stated in an earlier chapter of this dissertation and has appeared in numerous past studies and media planning texts (e.g., Kaplan & Shocker, 1971; Scissors & Surmanek, 1982; and Jugenheimer & Turk, 1980).

Table 11 (p.136) shows that the average adjusted gross rating points (AGRPs) in the media quantity discounts group is significantly higher than those in the no-discount group at high budget levels. The same results have also been found at low budget levels as Table 12 (p. 136) indicates. These differences in GRPs between the two groups are statistically significant at both budget levels. Therefore, Hypothesis 4 has been rejected in his study.

To test an impact of the use of media quantity discounts on vehicle selections and their insertions, contingency tables have been developed and listed in Table 23 (p.161) and Table 24 (p. 162). At the high budget levels, the results indicate that the

optimum solutions from a model with media quantity discounts recommend more vehicle insertions than those from a model without media quantity discounts, and that the model that examined the media quantity discounts recommended less a lower CPM magazine (Table 23). However, no significant difference has been found in the test of the impact on vehicle selection at the low budget levels. If the significance level is relaxed to the .30 level, the difference in the optimum schedules between the two models would have been significant. Therefore, the present study partially rejects Hypothesis 10.

The results clearly indicate that the media quantity discounts variable is essential in the media selection process. Although this variable is not sensitive enough to make a difference in vehicle selections when the advertising budget is small, the omission of this variable could jeopardize the validity of the optimum schedule. Even at the low budget levels, the difference in vehicle selections would have been significant if the significance level was .30. This means that the media quantity discounts variable is heavily involved in the media selection process. These findings are also consistent with past findings. The use of media quantity discounts means a reduced unit cost of a vehicle so as to increase vehicle purchase. The present study has shown that the loss of Adjusted GRPs (AGRPs) due to the omission of the media quantity discounts option in the model is 15.1 points on the average. Considering the average AGRPs estimated in the optimum schedules of the present analyses was 127.9, the media planner would get 11.8 percent less GRP producing schedules by using a model that neglects this option. Therefore, the present study strongly recommends that this variable be adopted in the media selection model.

Carryover Effect

Use of Carryover Effects

In Chapter 2, a review of the leading media planning texts indicated that the consideration of carryover effect in estimating the media impact of the schedule is important since the advertising exposure in a particular time period will be carried over to the subsequent period and the carryover effect is a deciding factor in the timing of advertising. In addition, the empirical findings have suggested that the size of the carryover effect can be determined based on the various types of creative factors (e.g., Laband, 1989; Underwood & Schultz, 1967; and Strong, 1914). Yet, the extent to which this element is significant in the media selection process is still unclear. Hypothesis 5 and Hypothesis 11 test the importance of this element.

To test an impact of carryover effect on Adjusted GRPs (AGRPs), Hypothesis 5 states that there will be no difference between the estimated value of AGRPs from the model that estimates the size of the GRPs in each schedule considering advertising carryover effect and the one from the model that estimates the size of the GRPs in each schedule without considering advertising carryover effect, if all other factors held constant for high and low budget levels. Concerning the test of an impact of carryover effect on vehicle selection, Hypothesis 11 argues that there will be no difference in the selection of the vehicles and their insertions between the results from the model that does not consider carryover effect and those from the model that does, if all other factors are held constant for high and low budget levels.

Earlier, the present study has shown that no differences in AGRPs have been found between in the solutions from a model which estimates the media impact considering carryover effect and in the solutions from a model without carryover effect

at both budget levels (Table 13, p. 139 and Table 14, p. 139). Therefore, Hypothesis 5 has been accepted.

Concerning the test of the impact of carryover effect on vehicle selections, the present study has shown the results in Table 25 (p. 164) and in Table 26 (p. 165). At the high budget levels, the results indicate that there is no difference in the vehicle selection of the optimum solutions between the two treatment groups. However, the present study has found the significant impact of carryover effect on the vehicle selections at the low budget level. The maximum GRP schedules suggested from the model that applies the carryover effect were different from those from the model without carryover effect in terms of advertising budget allocations through months and the vehicle preference of the optimum schedules. Therefore, the present study partially rejects Hypothesis 11. The results of the test of the impact of carryover effect at the low budget level mean that the difference of vehicle selections caused by adopting this variable does not create much difference in Adjusted GRPs (AGRPs). In other words, although the recommended schedules became slightly different by using this variable in the model, the difference in vehicle selections was not translated into media impact. If the two slightly different schedules suggests virtually the same media impact, it is the author's belief that any of these two schedules can be recommended for the upcoming advertising campaign. Therefore, the author believes that the carryover effect can be omitted in the optimization model for the sake of the parsimony of the model. This is because the largest GRP producing schedules recommended from a model that does not consider carryover effect option generates almost the same media impact as the optimum schedules recommended from a model with carryover effect option does.

In summary, the current study has found that the carryover effect variable does not affect the media selection process. However, the results can be valid only when the

product has no seasonality. Since the present analysis has been conducted without the assumption of seasonality, the effectiveness of this variable when seasonality is involved is still unknown. Otherwise, this variable can be omitted from the model.

Degree of Carryover Weights

As shown in Chapter 2, the empirical findings suggest that the size of the carryover rates could vary depending on the various message factors other than the exposures themselves. Then, the question of how different rates of carryover effect could affect in the media selection process needs to be tested. Hypothesis 6 expects that there will be no difference between the estimated value of adjusted gross rating points (AGRPs) from a model that applies the low carryover rates and the one from a model that applies the high carryover rates, if all other factors are held constant for high and low budget levels. Concerning the test of the size of carryover weight on vehicle selections, Hypothesis 12 argues that there will be no difference in the selection of the vehicles and their insertions between the results with the low carryover rates and those with high carryover rates, if all other factors are held constant for high and low budget levels.

ANOVA test results indicate that the mean value of adjusted gross rating points (AGRPs) for a group with high carryover weight is not statistically different from that for a group with low carryover weight at both budget levels (Table 15, p. 142, and Table 16, p. 142). Therefore, Hypothesis 6 has been accepted.

As discussed in the earlier section of this chapter, the present research has also found that there is no difference in the vehicle selections and their solutions between the two groups at the low budget levels (Table 28, p. 169). However, the present study

has found the impact of the various sizes of carryover rates on the choice of the two magazines in the optimum schedules (Table 27, p.168). This impact was significant, according to the Chi-square test. Therefore, Hypothesis 12 has been partially rejected.

The findings reveal that the model suggests slightly different optimum schedules depending on the size of the carryover rate the model applies but these different schedules generate almost the same adjusted gross rating points (AGRPs). These results are consistent with those from the test of Hypothesis 5 and Hypothesis 11, which tests whether the consideration of carryover effect in estimating GRPs of the media schedule in the model would affect the vehicle selections of the maximum GRP schedules. With the same reasoning, the author believes that this variable can be omitted from the model.

Conclusion of the Test of the Carryover Effect in the Media Selection Process

As the findings of the hypotheses tests indicate, the consideration of carryover effect in estimating GRPs in the model makes vehicle selection slightly different in some cases, but this difference does not apply to the difference in Adjusted GRPs (AGRPs). In other words, this variable is not sensitive enough to make significant differences in the media selection process. Therefore, the present study concludes that this variable may be omitted from the model for the parsimony of the model. However, the results of the test of GRPs indicate that the GRPs of the optimum schedule becomes higher with the consideration of the carryover effect although the model suggests virtually the same vehicle selections whether the model considers this variable or not. Therefore, the model should re-estimate GRPs after the optimum schedule has been selected. Considering the fact that the accommodation of the carryover effect in the

model makes the media selection process much more complicated, this conclusion can be good news to model builders. By omitting this options, the models can be much faster in producing the largest GRP producing schedule. On the other hand, this conclusion is rather surprising to many media planning researchers. In relation to the timing of advertising, the consideration of the carryover effect in media planning is considered to be critical. The results indicate that this variable does not have much impact on the vehicle selection of the optimum schedule, although the accommodation of the carryover effect in estimating GRPs makes the overall media impact of the schedule higher, as the comparison of GRPs has indicated (Table 13 -16).

Summary of Hypotheses Tests

The results of the hypotheses tests discussed in the above section of this chapter have been summarized to better explain the impact of each element in the media selection process. Table 30 lists these results.

Table 30
Summary of Results of Hypotheses Tests

VARIABLE		HYPOTHESES	RESULTS	OVERALL CONCLUSION
Timing of Advertising	Objective Function	There will be no difference in the estimated impact between the solutions from the long-term optimization model and the solutions **that suggest the most impact of the continuous advertising (i.e., aggregate monthly optimization)**, if all other factors are held constant for high and low budget levels.	Rejected	The long-term optimization model is essential in the media selection process.
	Vehicle Selection	There will be no difference in the selection of the vehicles and their insertions between the results from the long-term optimization model and the solutions **that suggest the most impact of continuous advertising (i.e., aggregate monthly optimization).**	Rejected	
Use of Message Effect	Objective Function	There will be no difference between the estimated value of adjusted gross rating points (AGRPs) from the model that determines the optimum schedule based on vehicle gross rating points and the one from the model that determines the optimum schedule based on message gross rating points, if all other factors are held constant for high and low budget levels.	Partially Rejected	The author could not find an impact of the size of message weights, but found an effect of the use of message effect at the high budget level. The present study recommends inclusion of this variable in the media selection model.
	Vehicle Selection	There will be no difference in the selection of the vehicles and their insertions between the results from the model without the message effect option and those from the model with message effect.	Partially Rejected	
Degree of Message Weights	Objective Function	There will be no difference between the estimated value of adjusted gross rating points (AGRPs) from a model that applies the low message weights and the one from a model that applies the high message weights.	Partially Rejected	
	Vehicle Selection	There will be no difference in the selection of the vehicles and their insertions between the results with the low message weights and those results with high message weights.	Accepted	

Table 29 (Continued)

Media Quantity Discounts	Objective Function	There will be no difference between the estimated value of adjusted gross rating points (AGRPs) from the model that calculates the scheduling cost considering the media quantity discounts and the one from the model which calculates the cost without considering the media quantity discounts, if all other factors are held constant for high and low budget levels.	Rejected	Found an impact of media quantity discounts in the media selection process
	Vehicle Selection	There will be no difference in the selection of the vehicles and their insertions between the results from the model that applies the media quantity discounts and those from the model which does not.	Partially Rejected	
Use of Carryover Effect	Objective Function	There will be no difference between the estimated value of adjusted gross rating points (AGRPs) from the model that estimates the size of the GRPs in each schedule considering advertising carryover effect and the one from the model that estimates the size of the GRPs in each schedule without considering advertising carryover effect, if all other factors held constant for high and low budget levels.	Accepted	Found minor impact of carryover effect in the media selection process, but this difference is considered to be negligible.
	Vehicle Selection	There will be no difference in the selection of the vehicles and their insertions between the results from the model that does not consider carryover effect and those from the model that does, if all other factors are held constant for high and low budget levels.	Partially Rejected	
Degree of Carryover Weights	Objective Function	There will be no difference between the estimated value of adjusted gross rating points (AGRPs) from a model that applies the low carryover rates and the one from a model that applies the high carryover rates, if all other factors are held constant for high and low budget levels.	Accepted	
	Vehicle Selection	There will be no difference in the selection of the vehicles and their insertions between the results with the low carryover rates and those with high carryover rates, if all other factors are held constant for high and low budget levels.	Accepted	

CHAPTER 9
SUMMARY, CONCLUSIONS, AND IMPLICATIONS

The goals of this study are 1) to develop a media selection framework that possesses the primary elements of the media selection process and that shows a global picture of how media selection works, and 2) to verify the role of each element in the model. In a situation where no comprehensive media selection modeling framework is available, developing such a framework allows model builders to evaluate past models both to give an idea of their performance and to reveal a direction for the future development of the media selection model.

Based on a content analysis of seven major media planning texts, the author has determined the elements that are important in the media selection process and has proposed a normative media selection model. A content analysis has identified the elements that are essential in the media selection process, but the role of each element in the media selection process is still unknown. To figure out the role of each element in the process, the author has conducted a verification analysis. This verification analysis is crucial because it enables researchers to know why the model, and each element in the model, is so important and how each element is performing in the media selection process. This test also enables researchers to eliminate some elements which do not make a significant impact on the process. Despite the fact that an element is conceptually important in the media selection process, an element may be eliminated if it does not affect the structure of the optimum schedule.

Due to both the complexities involved in this subject and the lack of past research, the validation of the model is limited to the scope of consumer magazines and

to the elements that are directly involved in the estimation of media impact. The elements tested include: timing of advertising, media quantity discounts, message effect, and carryover effect.

Timing of advertising concerns the importance of the model's ability to consider different timing patterns in selecting the media schedule with the most impact. Conceptually, the consideration of the *media quantity discounts* is important because it facilitates the volume purchase of a certain vehicle by lowering the unit cost of a vehicle when advertised frequently. In other words, the cost efficiency of each vehicle varies depending on the frequency of its purchase. This study tests how the examination of this element in the model will affect the outcome of the optimum solution. *Message effect* concerns the importance of the model's ability to estimate the media impact in terms of exposure to the advertisement rather than in terms of exposure to the vehicle. Finally, *carryover effect* refers to the amount of advertising carried over to the subsequent time period. Since this element is conceptually important in scheduling the media plan, this study tests its influence in determining the optimum schedule.

To verify the model, a computer program that reflects the normative model was developed. This model selects the schedule generating the most media impact based on gross rating points (GRPs), which reflect the sum of the rating points of all insertions in the schedule. Through the review of the empirical findings related to each element, this study has determined the operational definition of each element and the empirical relationship among elements in the model.

By analyzing a total of 720 optimum schedules produced from the computer model with different treatments, this study has determined whether the use of any element in the model makes the <u>vehicle selection</u> of the optimum schedule different and whether such different vehicle selection influences the <u>media impact</u> (i.e., Adjusted

Gross Rating Points). To illustrate, a certain independent variable should be effective in two ways in order for a variable to have any impact in the media selection process: 1) the vehicle selection of the schedule generating the most media impact from a model that incorporates a certain independent variable is quite different from the vehicle selection from a model that does not incorporate a variable, and 2) these two vehicle selections (i.e., schedules) estimate the different AGRPs.

The test of significance of each independent variable on media impact initially focused on the average value of AGRPs. AGRPs are the gross rating points (GRPs) of the schedule generating the most media impact, re-estimated with constant carryover and message weight. The average value of AGRPs has given descriptive information of what effect the difference in the selection of the vehicles caused by the use of an independent variable made in terms of the value of AGRPs. Then, to see if such difference in AGRPs is statistically significant, analysis of variance (ANOVA) tests have been conducted.

Contingency tables of the frequency of vehicle insertions have been formed for the test of significance of each independent variable on the selection of vehicles and their insertions. These tables show the sum of the frequency of insertions recommended in all the optimum schedules related to a certain treatment group, as well as the total percentage of each frequency. These tables give a global view of the heterogeneity of the vehicle selections by comparing the solutions obtained from a model which examined a certain independent variable with the solutions obtained from a model which did not examine such variable. Then, to see if such heterogeneity is statistically significant, Chi-square tests have been conducted since the dependent variable (i.e., frequency of vehicle insertions) in this validation is considered as a

nominal variable. Any elements that affect the vehicle selection and the media impact have been considered to be effective in the media selection process.

The study found a decisive effect of the timing of advertising on the media selection process. When the model evaluates all the possible types of advertising schedules (i.e., the long-term optimization model), the model was able to recommend a more effective optimum schedule than the model which evaluates continuous schedules. This was true for high and low budget levels. The solutions from the long-term optimization model had a consistent pattern of vehicle selections in the optimum solutions. Table 31 summarizes the vehicle selections of the long-term optimization analysis. This table shows that the long-term optimization model, which produces a higher media impact solution than the model that evaluates continuous schedules, recommends heavy advertising in the earlier campaign period. In fact, the long-term

Table 31
Average Vehicle Insertions for Long-term Optimum Schedules[a]

	Month						Total
	1	2	3	4	5	6	
Magazine 1	0.42 (4.0[c])	0.23 (2.2)	0.18 (1.7)	0.13 (1.3)	0.11 (1.0)	0.04 (0.4)	1.12 (10.6)
Magazine 2	1.92 (18.2)	1.83 (17.3)	1.78 (16.9)	1.60 (15.1)	1.34 (12.8)	0.96 (9.1)	9.43 (89.4)
Total	2.34 (22.2)	2.06 (19.5)	1.96 (18.6)	1.73 (16.4)	1.45 (13.8)	1.01 (9.5)	10.55[b] (100.0)

[a] The table reflects the average insertion of the magazines recommended for 360 long-term optimum schedules. "Long-term optimum schedules" mean that the timing of advertising is considered in determining the most GRP producing schedules.

[b] 10.55 represents the mean of a total number of magazines per schedule recommended from the total of 360 optimum advertising schedules.

[c] Total percentage in parenthesis. For example, 360 optimum solutions in total recommends 4.0% for Magazine 1 (i.e. high CPM magazine) in Month 1.

optimization model recommends 60.3 percent of advertising for the first three months. If the model had examined the seasonality factor, the imbalance in vehicle distributions across the time frame would have been greater.

In addition, the present study has also found that the estimation of the media schedule in the message GRPs (i.e., message effect) and the consideration of the media quantity discounts in calculating the schedule cost in the media selection model has some impact in the media selection process at high budget levels. However, the maximum GRP schedules did not become different at low budget levels with the use of message effect and with the application of media discounts. Furthermore, this study has found that the schedule generating the most media impact does not change in spite of the use of the carryover effect, and of the size of the carryover weights, at both budget levels.

The author concludes that timing of advertising is essential in the media selection process. A model which produces a monthly optimum schedule and which recommends the same schedule month after month will produce less efficient long-term optimum solutions. Concerning message effects and media quantity discounts, which have some impact in the media selection process at high budget levels, the author believes these variables were not sensitive enough to make a difference in vehicle selection when the advertising budget is small. However, the importance of these variables is likely to be greater in the optimization with more comprehensive databases, even with a small advertising budget. So, the author is very reluctant to omit variables like media quantity discounts and message effect, even at the low budget levels. This study concludes that media quantity discounts and message effect are important elements in the media selection process.

Carryover effect is a conceptually important element in the media selection process, but this study has found that this variable has little impact in selecting the schedule generating the most media impact. Therefore, for the sake of parsimony of the model, this variable may be omitted in the optimization stage. However, the insignificance of carryover effect in the media selection process could only mean that the vehicle selection of the schedule generating the most media impact does not change with the examination of carryover effect in the model. When more than a million schedule options are compared to determine the optimum schedule, carryover effect may not be considered since it does not change the structure of the optimum schedule. Yet, a correct estimation of media impact of the optimum schedule cannot be achieved without this variable.

Table 32 shows the difference in GRPs caused by omitting carryover effect. This table shows that even the carryover effect that is proven to be ineffective in the vehicle selection of the optimum schedules makes a significant difference in the estimation of the media impact. For example, the model that does not consider carryover effect in the estimation of GRPs at the high budget level would estimate 77 gross rating points lower than the model with carryover effect would estimate.

Table 32
Comparison of Gross Rating Points of the Optimum Schedules Among Treatments

Independent Variable	Budget Levels	Comparison of GRPs of Optimum Schedules			
		When a variable is examined in the model	When a variable is not examined in the model	High Weight	Low Weight
Carryover Effects	High	170.4	93.4	180.8	160.0
	Low	120.4	68.2	132.8	107.9

The author believes that carryover effect should be considered in the estimation of the media impact unless the omission of this variable does not affect the value of the media impact. Since the examination of carryover effect makes the media impact of the optimum solution higher, the model should estimate GRPs with the consideration of carryover effect. To summarize, the model may omit carryover effect in the selection of the optimum schedule to reduce the computation time, but the media impact of the optimum schedule should be re-estimated after the optimum schedule has been obtained.

The findings of this study have several implications for media theorists, media selection model builders, and media practitioners. The current study has developed a normative media selection model that embraces the primary elements in the media selection process. In other words, what the present study has done in the explanation of the media selection problem is to propose the general model and to verify it. The author believes that this framework provides a clear, simple, and concrete view of an ever-challenging media selection problem. In addition, such a framework can be a foundation to organize micro-theories of general media selection models that explain the elements in the model and the relationship among elements. In fact, through the operational definition of each concept and analysis among concepts in the model, the author has also shown how the many micro-theories from psychology, economics, and advertising can be applied to explain the size of message weight, the size of the carryover weight, the cognitive carryover effect, or the types of the carryover effect, among others, in this normative media selection framework.

Media selection model builders should also benefit from the findings of this study. The author has first suggested the general framework of the media selection process which incorporates the primary elements in the media selection process. By

suggesting such a framework, the author has pointed out that the media selection process should reflect the media planning process and a good media selection model is the one that represents the media planning process well. This framework defines the boundaries of the media selection process and suggests the key elements in the model.

A general consensus on the criteria of better media selection models is essential in this field because it allows model builders to move in the same direction. And, the author believes this study has provided a foundation for such a consensus. Model builders should also appreciate the findings of the verification of the normative media selection model. They are now able to estimate the significance of each element in the media selection process. These findings should help model builders determine the nature of the media selection process. Also, this study warns of the danger of losing media impact by omitting a variable which is important in this process. All these results should help to develop better and more reliable future media selection models.

Media directors who want to improve media selection procedures should also appreciate the findings of this study. They are now able to systematically consider timing of advertising, media quantity discounts, and message effect as key variables in selecting media categories and vehicles. Practitioners also know that carryover effect is not quite important in determining the media schedule, but it is important in estimating media effects. Planners can also recognize the extent of loss they would take by neglecting an element that is proven to be effective in the media selection process. For example, Table 33 exhibits the idea of how much of the monetary effectiveness the recommended optimum schedule would lose without examining these important variables in the model.

For each element in the model, and for each budget level, this table illustrates the loss of adjusted gross rating points (AGRPs) in different treatments, and the

Table 33
Impact of Timing of Advertising, Media Quantity Discounts, and Message Effect In the Media Selection Process, and Their Economic Values

Variable	Budget Level	Sample Size	Adjusted GRPs: Difference* $AGRP_2$-$AGRP_1$	Adjusted GRPs: Economic Value	Average Advertising Budget	Percent of Economic Value to Adv. Budget
Timing of Advertising	High	360	42.1	$ 357,426	$ 852,389	37.5 %
	Low	360	31.3	286,707	573,472	40.0
Media Quantity Discounts	High	180	17.5	109,874	839,444	12.5
	Low	180	13.1	78,992	551,739	12.7
Use of Message Weights	High	180	18.8	121,490	839,444	12.5

* The difference between AGRPs of the optimum solutions from a model with a variable and those from a model without a variable

financial value of these losses, by not considering the variables that are found to affect the media selection process. In other words, for the variables which are now shown to make a difference in vehicle selections, this table shows the difference in GRPs and their economic value attributable to alternative vehicle selections. The method of obtaining a monetary value can be expressed as the following formula:

$$\text{Value} = (\text{Budget}/\ AGRP_1)*(AGRP_2-AGRP_1) \qquad (1)$$

where: $AGRP_1$ = Adjusted GRPs from a model without an element

$AGRP_2$ = Adjusted GRPs from a model with an element

Source: The Media Group (1989). Optimizing Media Plans. Special Advertising Working Paper, Department of Advertising, University of Florida: Gainesville, Florida.

The monetary value can be calculated by multiplying the difference of adjusted gross rating points (AGRPs) in solutions from a model that examines an element, versus those from a model that does not examine an element, by the value of each gross rating point achieved without employing an independent variable. As Table 33 shows, the cost of omitting a significant variable, on the average, is indeed great. For example, at high budget levels, AGRPs of the optimum solutions chosen from a model which does not examine media quantity discounts for consumer magazines in calculating the schedule costs can generate a schedule whose effectiveness is 17.5 points lower than the maximum impact attainable with quantity discounts. In addition, this difference in AGRPs represents about $109,874 worth of additional gross rating points, or 12.5 percent of the average advertising budget. By examining this variable, the model is able to identify the schedule which has more vehicle insertions and to represent more media impact. This is possible since the unit cost of a magazine tends to be lowered when volume purchase is involved.

Without considering this variable, the model is not able to figure out the change of the unit costs. Considering that the average advertising budget for the optimum schedules recommended in this study was $839,444 at the high budget level, this $109,874 represents 12.5 percent more economic value. At the low budget level, the difference represents 14.5 percent more economic value. Not surprisingly, this finding is consistent with that of the Kaplan & Shocker (1971) study which reported that a model without this variable suggests a schedule whose effectiveness is 12 percent below the maximum obtainable. Accommodation of such elements into the model makes the model more complex, but the benefits of doing this is well worth the effort.

These findings can also provide media selection heuristics to media practitioners. The present study has already shown that duplicated monthly optimum

solutions, which are continuous advertising schedules, have produced less media impact than the long-term optimum solutions which turned out to be pulsing or flighting schedules (Table 31, p.195). Therefore, it seems certain that using continuous advertising schedules is not the best way to allocate an advertising budget (Table 31, p.195). However, this may not be a generalization of other media categories and budgets. More research is needed.

Therefore, even when media practitioners are reluctant to use computer models in media planning, or such models are not available to them, the findings of the present study should help them choose better timing patterns for their campaign. Now, practitioners can further recognize the importance of computer modeling and become more knowledgeable in selecting a media schedule.

The author believes that the present study has provided a great amount of knowledge on the nature of the media selection process. Although this is just a beginning of ever-challenging media selection research, in that the study has only verified a model with a single media category, this study can be a solid foundation for future research.

APPENDIX A
BASIC PROGRAM FOR SINGLE MEDIA CATEGORY SELECTION MODEL

```
REM  ##############################################################
REM       THIS PROGRAM IS TO DEVELOP LONG-TERM
REM       OPTIMIZATION SCHEDULES IN CONSUMER MAGAZINES.
REM  ##############################################################

    DIM   MBD(12,12,5), VCOST(5,12), CBD1(51),CBD2(51),CBD(51), L(12)
    DIM VM(10,10),GCBD(12),VIN(10,10), CRT1(12),CRT2(12),CRT3(12),GGRP(7)

    DEFINT I,J,X,P

    TINST=0:GRP=0:r2isum=0:TCOST=0

REM  ********************************
REM       PROGRAM INTRODUCTION
REM  ********************************

    OPEN "SCRN:" FOR OUTPUT AS #1
       GOSUB PRINTRO:
    CLOSE#1

INPP:
    DIM rij(5,5),E(11),ABD(20), C(5),CP(5)

REM  ******************************
REM       ASKING USE OF OPTIONS
REM  ******************************

    PRINT  "Do you want to create a NEW schedule OR use the existing file? "
    INPUT  "1) for new schedule 2) for the other";AA
    CLS

REM  *****************************
REM       DATA IMPORT OR ENTRY
REM  *****************************

    ON AA GOSUB CREATE,USE

    INPUT "USE OF MEDIA DISCOUNTS? 1) YES, 2) NO"; MD
    PRINT
    INPUT "INPUT BUDGET WEIGHT (HIGH;.6, LOW;.4)"; BUD
    PRINT
    INPUT "INPUT MESSAGE WEIGHT (HIGH;.6, LOW;.4, NO WEIGHT;1)"; MW
    PRINT
    INPUT "INPUT CARRYOVER WEIGHT (HIGH;.55, LOW;.35; NO WEIGHT;0)"
```

```
        ;CRW
    PRINT
    INPUT "USE OF TIME FRAME? 1) YES, 2) NO"; TF
    PRINT

    FOR I=0 TO V-1
        ri(I)=MW*ri(I)
        r2i(I)=MW*r2i(I)
    NEXT I

    FOR I=0 TO V-2
        FOR J=I+1 TO V-1
            rij(I,J)=MW*rij(I,J)
        NEXT J
    NEXT I

    GOSUB PAUSE3

REM ***************************
REM         MAIN ESTIMATION
REM ***************************

REM     --------------------------------
REM         BBD CALCUATION
REM     --------------------------------

REM To get Self-pair

    GOSUB SELF:

REM To get cross-pair and main calculation

    GOSUB CROSS:

    REACH1=(1-E(0))*100
    REACH3=(1-E(0)-E(1)-E(2))*100
    AF=GRP*100/REACH1
    GI=GRP*TSIZE
    CPM=TCOST/GI

REM     ---------------------------------------------------
REM         RESULT OUTPUT STAGE
REM     ---------------------------------------------------

    OPEN "SCRN:" FOR OUTPUT AS #2

    PAUSE5:
        IF INKEY$="" THEN PAUSE5
        CLS
    CLOSE #2

FIN1:
    CLS

    INPUT " Do you want to print an output (1:yes, 2:no)";AA
```

```
    ON AA GOTO RESULT,OPT

RESULT:

    OPEN "LPT1:" FOR OUTPUT AS #2
        ON ERROR GOTO FIN1
        GOSUB PRINTOUT:
    CLOSE #2

OPT:
    NUM=1

    FOR I=0 TO V-1
        NUM=NUM*(VINST(I)+1)
    NEXT I

    PRINT "Number of schedules to be evaluated in a single month"
    PRINT NUM
    PRINT
    PRINT "Total number of schedule"; NUM^6
    PRINT

    INPUT "Do you want to optimize (1:yes, 2:no)";AA

    IF AA=2 GOTO DDD

AGAIN:
    ULIMIT=TCOST*6*BUD
    PRINT USING "UPPER BUDGET LIMIT:  $###,###,###.##";ULIMIT
    LLIMIT=ULIMIT*.9

    PRINT USING "LOWER BUDGET LIMIT:  $###,###,###.##";LLIMIT
    GOSUB PAUSE3

REM   ********************************************
REM        OPTIMIZAITON WITH NO TIME FRAME
REM   ********************************************

    IF CRW=0 THEN GOSUB NWEIGHT ELSE GOSUB WEIGHT:

    IF TF=1 THEN GOTO TTOPT:

    GOSUB SINOPT

    GOSUB SBBD

    IF TIN=0 THEN GOTO SZERO
    rbar1=0
    rbar1=SBEST/TIN
    rijsum=0

    GOSUB SCPAIR

    GOSUB SABMBD
```

```
    GOTO YNEXT

SZERO:
    MBD(SCOUNTER+2,0,0)=1
    MBD(SCOUNTER+2,0,1)=1
    MBD(SCOUNTER+2,0,2)=1
    MBD(SCOUNTER+2,0,3)=1

YNEXT:

    A=SCOUNTER+2:B=SCOUNTER+2:C=SCOUNTER+2:D=SCOUNTER+2:

    GOSUB CARRY

    NTGRP=0

    FOR I=0 TO K
        NTGRP=NTGRP+CBD(I)*I
    NEXT I

    BEST=NTGRP*6

    FOR J=0 TO V-1
        FOR I=1 TO 6
            VM(I,J)=SVIN(J)
        NEXT I
    NEXT J

    GOTO POUT

TTOPT:

REM   ******************************
REM       OPTIMIZATION
REM   ******************************

REM   --------------------------------
REM       SINGLE MONTH
REM   --------------------------------

    COUNTER=0

    FOR V3=0 TO VINST(2)
        FOR V2=0 TO VINST(1)
            FOR V1=0 TO VINST(0)
                COUNTER=COUNTER+1
            REM To adjust the vehicle insertions in each routine

                VIN(COUNTER,0)=V1
                VIN(COUNTER,1)=V2
                VIN(COUNTER,2)=V3

                GOSUB SPAIR:
                IF TIN=0 THEN GOTO ZEROM1
```

```
                rbar1=0
                rbar1=GRP/TIN

            REM TO GET CROSS-PAIR

                rijsum=0
                GOSUB CPAIR:
                GOSUB ABMBD
                GOTO ZEROM2

    ZEROM1:
                MBD(COUNTER,0,0)=1
                MBD(COUNTER,0,1)=1
                MBD(COUNTER,0,2)=1
                MBD(COUNTER,0,3)=1

    ZEROM2:
                IF COUNTER=NUM THEN GOTO PLONG
            NEXT V1
        NEXT V2
    NEXT V3

REM   ------------------------------------------------
REM         LONG-TERM OPTIMIZATION
REM   ------------------------------------------------

PLONG:
    COUNT=0
    BEST=0
    PARK=0
    PARK2=0

    FOR M6=1 TO COUNTER
      FOR M5=1 TO COUNTER
        FOR M4=1 TO COUNTER
          FOR M3=1 TO COUNTER
            FOR M2=1 TO COUNTER
              FOR M1=1 TO COUNTER
                  COUNT=COUNT+1

              REM BUDGET WINDOW PHASE

                  YCOST=0

                  FOR I=0 TO V-1
                      XX=VIN(M1,I)+VIN(M2,I)+VIN(M3,I)+VIN(M4,I)+VIN(M5,I)+VIN(M6,I)
                      YY=XX
                      IF MD=2 THEN XX=1
                      YCOST = YCOST + (YY)*VCOST(I,XX)
                  NEXT I

                  IF YCOST<LLIMIT THEN GOTO NEXTS
                  IF YCOST>ULIMIT THEN GOTO NEXTS

                  PARK=PARK+1
```

```
    PRINT COUNT

REM CARRY-OVER EFFECTS
REM MONTH1

    A=M6:B=M5:C=M4:D=M1

    GOSUB CARRY:

    GGRP(1)=0

    FOR I=1 TO K
        GGRP(1)=GGRP(1) + CBD(I)*I
    NEXT I

REM MONTH2

    A=M1:B=M6:C=M5:D=M2

    GOSUB CARRY:

    GGRP(2)=0

    FOR I=1 TO K
        GGRP(2)=GGRP(2)+CBD(I)*I
    NEXT I

REM MONTH3

    A=M2:B=M1:C=M6:D=M3

    GOSUB CARRY:

    GGRP(3)=0

    FOR I=1 TO K
        GGRP(3)=GGRP(3)+CBD(I)*I
    NEXT I

REM MONTH4

    A=M3:B=M2:C=M1:D=M4

    GOSUB CARRY:

    GGRP(4)=0

    FOR I=1 TO K
        GGRP(4)=GGRP(4)+CBD(I)*I
    NEXT I

REM MONTH5

    A=M4:B=M3:C=M2:D=M5
```

```
                GOSUB CARRY:

                GGRP(5)=0

                FOR I=1 TO K
                    GGRP(5)=GGRP(5) + CBD(I)*I
                NEXT I

            REM MONTH6

                A=M5:B=M4:C=M3:D=M6

                GOSUB CARRY:

                GGRP(6)=0

                FOR I=1 TO K
                      GGRP(6)=GGRP(6) + CBD(I)*I
                NEXT I

            REM CALCULATE GLOVAL GRPs

                GOGRP=0

                FOR I=1 TO 6
                      GOGRP=GOGRP+GGRP(I)
                NEXT I

                IF BEST<GOGRP THEN BEST=GOGRP ELSE GOTO NEXTS

                FOR I=0 TO V-1
                    VM(1,I)=VIN(M1,I)
                    VM(2,I)=VIN(M2,I)
                    VM(3,I)=VIN(M3,I)
                    VM(4,I)=VIN(M4,I)
                    VM(5,I)=VIN(M5,I)
                    VM(6,I)=VIN(M6,I)
                NEXT I

            NEXTS:
            NEXT M1
          NEXT M2
        NEXT M3
      NEXT M4
    NEXT M5
  NEXT M6

POUT:

  GOSUB FINAL

  CLS
```

```
REM  -----------------------------------------------------
REM       OPTIMIZATION OUTPUT PHASE
REM  -----------------------------------------------------

    OPEN "SCRN:" FOR OUTPUT AS #3
        GOSUB PRINTOPT
    CLOSE #3

REM  ---------------------------------------------
REM       OPTIMIZATION PRINTING
REM  ---------------------------------------------

FIN:
    INPUT  "Do you want to print the results (1. Yes, 2. no)"; BB
    IF BB=2 GOTO  DDD

    OPEN "LPT1:" FOR OUTPUT AS #3
        ON ERROR GOTO FIN
        GOSUB PRINTOPT
    CLOSE #3

DDD:

    INPUT "Do you want to run this program, again (1. Yes, 2. No)";CC
    IF CC=1 THEN GOSUB CLEAN
    IF CC=1 THEN GOTO INPP

    LOCATE 12,25
    PRINT "GOOD BYE!"
END

    ++++++++++++++++++++++++++++++++++++++++++++++++++++++++
    ++++++++++++++++++++++++++++++++++++++++++++++++++++++++

REM  **************************
REM       DATA INPUT
REM  **************************

CREATE:

    INPUT "How many vehicles in your schedule";V
    INPUT "Target Size";TSIZE

    GOSUB PAUSE3

    PRINT "Type vehicle name,vehicle insertion,ratings, and self-pair"

    FOR I=0 TO V-1
        INPUT VNAMES(I),VINST(I),ri(I),r2i(I)
    NEXT I

    IF V=1 THEN GOTO I1

    FOR I=0 TO V-2
        FOR J=I+1 TO V-1
```

```
            PRINT USING "INPUT ## AND ##  CROSS PAIR";I+1,J+1
            INPUT rij(I,J)
        NEXT J
    NEXT I

    I1:
    FOR I=0 TO V-1
        PRINT
        PRINT USING "INPUT ##TH VEHICLE COST";I+1

        FOR J=1 TO 6*VINST(I)
            PRINT USING "##ST INSERTION";J
            INPUT VCOST(I,J)
            PRINT
        NEXT J
    NEXT I

    GOSUB PAUSE3

    OPEN TEXT$ FOR OUTPUT AS #3
        WRITE #3,V,TSIZE

        FOR I=0 TO V-1
            WRITE #3,VNAME$(I),VINST(I),ri(I),r2i(I)
        NEXT I

        IF V=1 THEN GOTO W1

        FOR I=0 TO V-2
            FOR J=I+1 TO V-1
                WRITE #3, rij(I,J)
            NEXT J
        NEXT I

    W1:
        FOR I=0 TO V-1
            FOR J=1 TO 6*VINST(I)
                WRITE #3,VCOST(I,J)
            NEXT J
        NEXT I
    CLOSE #3
RETURN

USE:
    TEXT$=FILES$(1)
    OPEN TEXT$ FOR INPUT AS #4
        INPUT #4,V,TSIZE

        FOR I=0 TO V-1
            INPUT #4, VNAME$(I),VINST(I),ri(I),r2i(I)
        NEXT I

        IF V=1 THEN GOTO I2

        FOR I=0 TO V-2
```

```
        FOR J=I+1 TO V-1
            INPUT #4, rij(I,J)
        NEXT J
    NEXT I

I2:
    FOR I=0 TO V-1
        FOR J=1 TO 6*VINST(I)
            INPUT #4,VCOST(I,J)
        NEXT J
    NEXT I

    CLOSE #4
RETURN

REM   *********************************
REM        BASIC CAL SUB-ROUTINE
REM   *********************************

SELF:

    r2isum=0:TINST=0:GRP=0:TCOST=0

    FOR I=0 TO V-1
        IF VINST(I)=1 OR VINST(I)=0 GOTO ZERO1
        N=VINST(I):R=2
        COMB=1

        FOR G=1 TO R
            COMB=COMB*((N-G+1)/(R-G+1))
        NEXT G

        C(I)=COMB:
        GOTO SKIP

    ZERO1:
        C(I)=0

    SKIP:
        XX=VINST(I)
        IF MD=2 THEN XX=1
        CP(I)=VCOST(I,XX)/(ri(I)*TSIZE)
        r2isum=r2isum+C(I)*r2i(I)
        TINST=TINST+VINST(I)
        GRP=GRP+VINST(I)*ri(I)
        TCOST=TCOST+VCOST(I,XX)*VINST(I)
    NEXT I
RETURN

CROSS:

    rbar1=GRP/TINST:rijsum=0

    FOR I=0 TO V-2
        FOR J=I+1 TO V-1
```

```
        rijsum=rijsum+VINST(I)*VINST(J)*rij(I,J)
    NEXT J
NEXT I

REM  ---------------------------------------------------------------------------------
REM        FROM HERE, TO GET ALPHA AND BETA IN BBD MODEL
REM  ---------------------------------------------------------------------------------

N=TINST:R=2
COMB=1

FOR G=1 TO R
    COMB=COMB*((N-G+1)/(R-G+1))
NEXT G

rbar2=(r2isum+rijsum)/COMB
A=(rbar1*(rbar2-rbar1))/(2*rbar1-rbar2-rbar1^2)
B=(A*(1-rbar1))/(rbar1):D=A+B
L=TINST:IF L>10 THEN L=10

REM THIS IS A CALCULATION SECTION

IF L=0 THEN  GOTO INPP
N=TINST

FOR I=0 TO L
    IF I=0 GOTO BBBD1
    ABD(I)=ABD(I-1)*(A+I-1)/(B+TINST-I)
    GOTO BBBD2:
    BBBD1:
    ABD=1

    FOR J=0 TO TINST-1
        ABD =ABD*(B+J)/(D+J)
    NEXT J

    ABD(0)=ABD
    GOTO BBBD4

BBBD2:
    R=I
    COMB=1

    FOR G=1 TO R
        COMB=COMB*((N-G+1)/(R-G+1))
    NEXT G

    E(I)=COMB*ABD(I)
    SUM10=SUM10+E(I)
    E(0)=1-SUM10

BBBD4:
NEXT I
RETURN
```

```
REM   *********************************
REM        OPTIMIZING SUB-ROUTINE
REM   *********************************

SPAIR:

    TIN=0:COSTS=0:GRP=0:r2isum=0

    FOR I=0 TO V-1
        TIN=TIN + VIN(COUNTER,I)
        IF VIN(COUNTER,I)=1 OR VIN(COUNTER,I)=0 GOTO CHO1
        N=VIN(COUNTER,I):R=2
        GOSUB COM:
        C(I)=COMB:GOTO CHO2

    CHO1:
        C(I)=0:

    CHO2:
        r2isum=r2isum+C(I)*r2i(I)
        GRP=GRP+VIN(COUNTER,I)*ri(I)
    NEXT I

    L(COUNTER)=TIN:IF L(COUNTER)>10 THEN L(COUNTER)=10
RETURN

CPAIR:
    rijsum=0

    FOR I=0 TO V-2
        FOR J=I+1 TO V-1
            rijsum=rijsum+VIN(COUNTER,I)*VIN(COUNTER,J)*rij(I,J)
        NEXT J
    NEXT I
RETURN

ABMBD:

    REM FROM HERE, TO GET ALPHA AND BETA IN BBD MODEL

    N=TIN:R=2
    IF TIN=1 GOTO MON1
    GOSUB COM:
    rbar2=(r2isum+rijsum)/COMB:GOTO MON2

    MON1:

    rbar2=0

    MON2:

    A=(rbar1*(rbar2-rbar1))/(2*rbar1-rbar2-rbar1^2)
    B=(A*(1-rbar1))/(rbar1):D=A+B
    SUM11=0:SUM12=0:SUM13=0:SUM14=0:MGRP=0
```

```
    REM THIS IS A CALCULATION SECTION

    SUM11=0

    FOR I=0 TO L(COUNTER):ABD=1
        IF I=0 GOTO BBD1
        ABD(I)=ABD(I-1)*(A+I-1)/(B+TIN-I):GOTO BBD3

    BBD1:

        FOR J=0 TO TIN-1
            ABD =ABD*(B+J)/(D+J)
        NEXT J

        ABD(0)=ABD
        GOTO BBD4

    BBD3:
        R=I
        IF TIN=1 GOTO BBD5
        GOSUB COM:GOTO BBD6
    BBD5:
        COMB=1

    BBD6:
        MBD(COUNTER,I,0)=COMB*ABD(I)
        MBD(COUNTER,I,1)= MBD(COUNTER,I,0)*CR1(I)
        MBD(COUNTER,I,2)= MBD(COUNTER,I,0)*CR2(I)
        MBD(COUNTER,I,3)= MBD(COUNTER,I,0)*CR3(I)

        SUM11=SUM11+MBD(COUNTER,I,0)
        SUM12=SUM12+MBD(COUNTER,I,1)
        SUM13=SUM13+MBD(COUNTER,I,2)
        SUM14=SUM14+MBD(COUNTER,I,3)
    BBD4:
    NEXT I

    MBD(COUNTER,0,0)=1-SUM11
    MBD(COUNTER,0,1)=1-SUM12
    MBD(COUNTER,0,2)=1-SUM13
    MBD(COUNTER,0,3)=1-SUM14
RETURN

COM:

    REM TO GET COMBINATION OF SELF-PAIR

    COMB=1

    FOR G=1 TO R
        COMB=COMB*((N-G+1)/(R-G+1))
    NEXT G
RETURN

WEIGHT:
```

```
    FOR I=1 TO 10
        CR1(I)=1-(1-CRW)*EXP(-.087*(I-1))
        CR2(I)=CR1(I)^2
        CR3(I)=CR1(I)^3
    NEXT I
RETURN

NWEIGHT:
    FOR I=1 TO 10
        CR1(I)=0
        CR2(I)=0
        CR3(I)=0
    NEXT I
RETURN

CARRY:
    K=0
    ERASE CBD

    FOR P=0 TO L(C)
      FOR X=0 TO L(B)
        FOR I=0 TO L(A)
          FOR J=0 TO L(D)
            K=I+J+X+P
            CBD(K)=CBD(K)+MBD(D,J,0)*MBD(A,I,1)*MBD(B,X,2)*MBD(C,P,3)
          NEXT J
        NEXT I
      NEXT X
    NEXT P
RETURN

REM    **************************************
REM         Optimization with No Time Frame
REM    **************************************

SINOPT:

    SCOUNTER=0:SUPPER=ULIMIT/6:SBEST=0

    FOR V3=0 TO VINST(2)
        FOR V2=0 TO VINST(1)
            FOR V1=0 TO VINST(0)
                SCOUNTER=SCOUNTER+1
                SCOST=0:SGRP=0
                IF MD=2 THEN GOTO NODIS
                SCOST=SCOST+V1*VCOST(0,V1)+V2*VCOST(1,V2)
                        +V3*VCOST(2,V3)
                GOTO YDIS

            NODIS:
                SCOST=SCOST+V1*VCOST(0,1)+V2*VCOST(1,1)+V3*VCOST(2,1)

            YDIS:
                IF SCOST>SUPPER THEN GOTO SNEXT
                SGRP=SGRP+V1*ri(0)+V2*ri(1)+V3*ri(2)
```

```
            IF SBEST<SGRP THEN SBEST=SGRP ELSE GOTO SNEXT
            SVIN(0)=V1
            SVIN(1)=V2
            SVIN(2)=V3

        SNEXT:
            IF SCOUNTER=NUM THEN GOTO ABCD
        NEXT V1
    NEXT V2
NEXT V3

ABCD:
RETURN

SBBD:
    TIN=0:COSTS=0:r2isum=0

    FOR I=0 TO V-1
        TIN=TIN + SVIN(I)
        IF SVIN(I)=1 OR SVIN(I)=0 GOTO SCHO1
        N=SVIN(I):R=2
        GOSUB COM:
        C(I)=COMB:GOTO Scho2

    SCHO1:
        C(I)=0:

    SCHO2:
        r2isum=r2isum+C(I)*r2i(I)
    NEXT I

    L(SCOUNTER+2)=TIN:IF L(SCOUNTER+2)>10 THEN L(SCOUNTER+2)=10
RETURN

SCPAIR:
    rijsum=0

    FOR I=0 TO V-2
        FOR J=I+1 TO V-1
            rijsum=rijsum+SVIN(I)*SVIN(J)*rij(I,J)
        NEXT J
    NEXT I
RETURN

SABMBD:

    REM FROM HERE, TO GET ALPHA AND BETA IN BBD MODEL

    N=TIN:R=2
    IF TIN=1 GOTO SMON1
    GOSUB COM:
    rbar2=(r2isum+rijsum)/COMB:GOTO SMON2

SMON1:
```

```
    rbar2=0

    SMON2:

    A=(rbar1*(rbar2-rbar1))/(2*rbar1-rbar2-rbar1^2)
    B=(A*(1-rbar1))/(rbar1):D=A+B
    SUM11=0:SUM12=0:SUM13=0:SUM14=0:MGRP=0

    REM THIS IS A CALCULATION SECTION

    FOR I=0 TO L(SCOUNTER+2):ABD=1
        IF I=0 GOTO SBBD1
        ABD(I)=ABD(I-1)*(A+I-1)/(B+TIN-I):GOTO SBBD3

    SBBD1:

        FOR J=0 TO TIN-1
            ABD =ABD*(B+J)/(D+J)
        NEXT J

        ABD(0)=ABD
        GOTO SBBD4

    SBBD3:
        R=I
        IF TIN=1 GOTO SBBD5

        GOSUB COM:GOTO SBBD6

    SBBD5:
        COMB=1

    SBBD6:
        MBD(SCOUNTER+2,I,0)=COMB*ABD(I)
        MBD(SCOUNTER+2,I,1)=MBD(SCOUNTER+2,I,0)*CR1(I)
        MBD(SCOUNTER+2,I,2)=MBD(SCOUNTER+2,I,0)*CR2(I)
        MBD(SCOUNTER+2,I,3)=MBD(SCOUNTER+2,I,0)*CR3(I)

        SUM11=SUM11+MBD(SCOUNTER+2,I,0)
        SUM12=SUM12+MBD(SCOUNTER+2,I,1)
        SUM13=SUM13+MBD(SCOUNTER+2,I,2)
        SUM14=SUM14+MBD(SCOUNTER+2,I,3)

    SBBD4:
    NEXT I

    MBD(SCOUNTER+2,0,0)=1-SUM11
    MBD(SCOUNTER+2,0,1)=1-SUM12
    MBD(SCOUNTER+2,0,2)=1-SUM13
    MBD(SCOUNTER+2,0,3)=1-SUM14
RETURN

CLEAN:
    ERASE VNAMES$
    ERASE VINST,VCOST,ri,CP,r2i,rij,MMBD,ABD,E,C
```

```
RETURN

REM   ***************************
REM        PRINTING SCREEN
REM   ***************************

PRINTRO:

    LOCATE 3,9
    PRINT #1, STRING$ (47,"*")
    LOCATE 4,10
    PRINT #1,"ADVERTISING LONG-TERM OPTIMIZATION"
    LOCATE 5,9
    PRINT #1, STRING$(47,"*")
    GOSUB PAUSE
RETURN

PAUSE:

    LOCATE 22,25
    PRINT #1, "Press anykey to continue."

    pause2:
    IF INKEY$="" THEN GOTO pause2
    CLS
RETURN

PAUSE3:

    LOCATE 22,25
    PRINT  "Press anykey to continue."

    pause4:
    IF INKEY$="" THEN GOTO pause4
    CLS
RETURN

PRINTOUT:

    PRINT #2
    PRINT #2
    PRINT #2, STRING$(33,"*")
    PRINT #2, SPC(5) "MAGAZINE SCHEDULE"
    PRINT #2, STRING$(33,"*")
    PRINT #2
    PRINT #2
    PRINT #2, "    Frequency (f) Distribution    "
    PRINT #2, STRING$(35,"-")
    PRINT #2
    PRINT #2, "Message"
    PRINT #2, STRING$(9,"-")
    PRINT #2
    PRINT #2, "f" SPC(10) "%f"
    PRINT #2, STRING$(5,"-") SPC(5) STRING$(9,"-")
```

```
    FOR I=0 TO 10
        PRINT #2, SPC(22) USING "##          ###.##%";I,E(I)*100
    NEXT I

    PRINT #2
    PRINT #2
    PRINT #2, STRING$(25,"-")
    PRINT #2, "*** Summary Evaluation***"
    PRINT #2, STRING$(25,"-")
    PRINT #2
    PRINT #2, "Message"
    PRINT #2, STRING$(9,"-")
    PRINT #2
    PRINT #2, USING "Reach                    :        ###.##%";REACH1"
    PRINT #2, USING "EFFECTIVE REACH          :        ###.##%  ";REACH3
    PRINT #2, USING "AVERAGE FREQUENCY:                ##.##    ";AF
    PRINT #2, USING "GRPs                     :        ###.# ";GRP*100
    PRINT #2, USING "CPM                      :        $###.##        ";CPM
    PRINT #2
    PRINT #2
    PRINT #2, "***Cost Summary***"
    PRINT #2, STRING$(25,"-")
    PRINT #2,
    PRINT #2, "Vehicle Name" SPC(7) "Rating" SPC(7) "CPM" SPC(7) " Insertions" SPC(7)
    "Cost"
    PRINT #2, "------------" SPC(7) "-----" SPC(7) "------" SPC(6) "----------" SPC(6) "-----"

    FOR I=0 TO V-1
        XX=VINST(I)
        IF MD=2 THEN XX=1
        PRINT #2, VNAME$(I),  USING "    #.###          $##.##            ###
        $#,###,###";ri(I),CP(I),VINST(I),VCOST(I,XX)
    NEXT I

    PRINT #2, TAB(35) "Total:", USING "       $##,###,###";TCOST
RETURN

PRINTOPT:

    PRINT #3, STRING$(44,"*")
    PRINT #3,SPC(8) "OPTIMIZATION OUTPUT"
    PRINT #3, STRING$(44,"*")
    PRINT #3
    PRINT #3
    PRINT #3
    PRINT #3,"GLOBAL GRPs  :                    ", USING "####.##"; BEST*100
    PRINT #3
    PRINT #3
    PRINT #3
    PRINT #3, "                   Month 1          Month 2          Month 3          Month 4
        Month 5          Month 6"
    PRINT #3, "---------          ---------  ---------  --------  --------  --------"

    FOR I=0 TO V-1
```

```
        PRINT #3,  VNAME$(I),USING "##        ##        ##        ##        ##
        ##"; VM(1,I),VM(2,I),VM(3,I),VM(4,I),VM(5,I),VM(6,I)
    NEXT I

    PRINT #3,
    PRINT #3,
    PRINT #3,TAB(4), "TOTAL COST  :", USING "$###,###,###,###"; TTCOST
    PRINT #3,
    PRINT #3,
    PRINT #3, "Upper limit:                 "ULIMIT
    PRINT #3, "Lower limit:                 "LLIMIT
    PRINT #3
    PRINT #3
    PRINT #3, USING "Use of Media Discounts (1. Yes, 2. No):  ##";MD
    PRINT #3, USING "Use of Message Weight (High-.6, Low-.4, No Weight-1):
            #.#";MW
    PRINT #3, USING "Use of Carryover Weight (High-.55, Low-.35, No Weight-
            0):  #.#"; CRW
    PRINT #3, USING "Use of Time Frame (1. Yes, 2. No);  ##"; TF
    PRINT #3, USING "Budget Weight (High-.6, Low-.4);  #.#";BUD
    PRINT #3
    PRINT #3
    PRINT #3, "TOTAL NUMBER OF EVALUATED SCHEDULES;          ";PARK
    PRINT #3
RETURN

FINAL:

    TTCOST=0

    FOR I=0 TO V-1
        NN = VM(1,I)+VM(2,I)+VM(3,I)+VM(4,I)+VM(5,I)+VM(6,I)
        YY=NN
        IF MD=2 THEN NN=1
        TTCOST=TTCOST+(YY)*VCOST(I,NN)
    NEXT I
RETURN

PAUSE8:

    IF INKEY$="" THEN pause8
    CLS
RETURN
```

APPENDIX B
SAMPLE OPTIMIZATION ANALYSES RESULTS

This appendix lists the sample results of the optimization analysis. Among a total of 720 solutions obtained for this study, the first two and the last two solutions in both Male and Female target audience groups are presented.

FEMALE ADULTS CASE #1

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Parade	35.3	43.9	44.0	1	$ 382,300
National Enquirer	13.2	18.5		2	43,700

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Applied
b. Message Effects: High message weight was applied
c. Carryover Effects: High carryover weight was applied
d. Timing of Advertising: Long-term Optimization Analysis
e. Budget Level: High

Upper Budget Level: $ 1,690,920

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Parade	1	0	0	1	1	0
National Enquirer	2	2	2	2	2	2

Total Cost: $ 1,598,223

Estimated Gross Rating Points (GRPs): 330.5
Estimated Adjusted Gross Rating Points (AGRPs): 276.8

FEMALE ADULTS CASE #2

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Time	11.9	17.2	19.3	1	$ 120,130
Star	8.5	11.8		2	34,860

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Applied
b. Message Effects: High message weight was applied
c. Carryover Effects: Low carryover weight was applied
d. Timing of Advertising: Long-term Optimization Analysis
e. Budget Level: High

Upper Budget Level: $ 683,460

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Time	1	1	0	0	0	0
Star	2	2	2	2	2	2

Total Cost: $ 641,852

Estimated Gross Rating Points (GRPs): 119.4
Estimated Adjusted Gross Rating Points (AGRPs): 122.3

FEMALE ADULTS CASE #359

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Family Circle	17.3	24.9	37.5	1	$ 76,080
TV Guide	26.1	33.1		2	104,600

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Not applied
b. Message Effects: No message weight was applied
c. Carryover Effects: Low carryover weight was applied
d. Timing of Advertising: Not considered
(i.e., Aggregate Monthly Optimization Analysis)
e. Budget Level: Low

Upper Budget Level: $ 684,672

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Family Circle	0	0	0	0	0	0
TV Guide	1	1	1	1	1	1

Total Cost: $ 627,600

Estimated Gross Rating Points (GRPs): 237.3
Estimated Adjusted Gross Rating Points (AGRPs): 152.2

FEMALE ADULTS CASE #360

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Redbook	9.6	14.1	21.4	1	$ 65,925
Woman's Day	14.9	22.0		2	73,035

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Not applied
b. Message Effects: No message weight was applied
c. Carryover Effects: No carryover weight was applied
d. Timing of Advertising: Not considered
(i.e., Aggregate Monthly Optimization Analysis)
e. Budget Level: Low

Upper Budget Level: $ 508,980

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Redbook	0	0	0	0	0	0
Jet	1	1	1	1	1	1

Total Cost: $438,450

Estimated Gross Rating Points (GRPs): 89.4
Estimated Adjusted Gross Rating Points (AGRPs): 83.0

MALE ADULTS CASE #1

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
National Geographic	14.6	19.8	28.9	1	$ 139,280
Reader's Digest	19.2	24.8		2	124,730

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Applied
b. Message Effects: High message weight was applied
c. Carryover Effects: High carryover weight was applied
d. Timing of Advertising: Long-term Optimization Analysis
e. Budget Level: High

Upper Budget Level: $ 1,399,464

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
National Geographic	0	0	0	0	0	0
Reader's Digest	2	2	2	2	2	2

Total Cost: $ 1,332,120

Estimated Gross Rating Points (GRPs): 290.5
Estimated Adjusted Gross Rating Points (AGRPs): 235.3

MALE ADULTS CASE #2

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Time	14.8	21.1	18.1	1	$ 120,130
Jet	3.9	5.3		2	16,709

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Applied
b. Message Effects: High message weight was applied
c. Carryover Effects: Low carryover weight was applied
d. Timing of Advertising: Long-term Optimization Analysis
e. Budget Level: High

Upper Budget Level: $ 552,773

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Time	1	1	0	1	0	0
Jet	2	2	2	2	2	1

Total Cost: $ 544,189

Estimated Gross Rating Points (GRPs): 81.7
Estimated Adjusted Gross Rating Points (AGRPs): 82.4

MALE ADULTS CASE #359

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Road & Track	3.7	5.5	7.4	1	$ 38,200
Sports Afield	4.0	6.1		2	124,730

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Not applied
b. Message Effects: No message weight was applied
c. Carryover Effects: Low carryover weight was applied
d. Timing of Advertising: Not considered
(i.e., Aggregate Monthly Optimization Analysis)
e. Budget Level: Low

Upper Budget Level: $ 196,320

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Road & Track	0	0	0	0	0	0
Sports Afield	1	1	1	1	1	1

Total Cost: $ 130,880

Estimated Gross Rating Points (GRPs): 36.4
Estimated Adjusted Gross Rating Points (AGRPs): 21.3

MALE ADULTS CASE #360

Data Base

Vehicle Name	Rating	Self-Pair Rating	Cross-Pair Rating	Maximum Insertions	Vehicle Cost
Car & Driver	4.3	6.3	18.7	1	$ 49,175
USA Weekend	14.9	19.1		2	165,680

Treatments for the Optimization Analyses

a. Media Quantity Discounts: Not applied
b. Message Effects: No message weight was applied
c. Carryover Effects: No carryover weight was applied
d. Timing of Advertising: Not considered
(i.e., Aggregate Monthly Optimization Analysis)
e. Budget Level: Low

Upper Budget Level: $ 913,284

Recommended Media Schedule

Magazines	Month 1	Month 2	Month 3	Month 4	Month 5	Month 6
Car & Driver	1	1	1	1	1	1
USA Weekend	0	0	0	0	0	0

Total Cost: $ 295,050

Estimated Gross Rating Points (GRPs): 25.8
Estimated Adjusted Gross Rating Points (AGRPs): 22.9

APPENDIX C
SINGLE AND PAIRWISE ISSUE RATINGS OF TOP 30 RATED MAGAZINES

C.1. ADULT FEMALES MARKET

U.S. Total : 92,184,000	Better Homes & Gardens	Cosmo-politan	Ebony	Family Circle	Glamour	Good House-keeping	House Garden	Ladies' Home Journal	Life	Madmoi-selle
Single Issue Rating	18.2	9.4	5.1	17.3	7.3	18.2	4.1	13.4	6.2	4.5
Self-Pair Rating	26.2	13.3	6.8	24.9	10.9	25.7	6.6	19.4	9.7	6.8
Better Homes & Gardens	26.2	25.5	22.5	30.1	23.7	30.3	21.1	27.6	23.0	21.7
Cosmopolitan	25.5	13.4	14.0	24.5	14.2	25.1	13.0	20.9	14.5	12.3
Ebony	22.5	14.0	6.8	21.9	12.0	22.6	8.9	18.1	10.8	9.4
Family Circle	30.1	24.5	21.9	24.9	22.7	29.7	20.4	26.3	22.0	20.8
Glamour	23.7	14.2	12.0	22.7	10.9	23.5	10.8	19.1	12.5	10.1
Good Housekeeping	30.3	25.1	22.6	29.7	23.5	25.7	20.9	26.3	22.6	21.4
House Garden	21.1	13.0	8.9	20.4	10.8	20.9	6.6	16.4	9.7	8.3
Ladies' Home Journal	27.6	20.9	18.1	26.3	19.1	26.3	16.4	19.4	18.1	17.0
Life	23.0	14.5	10.8	22.0	12.5	22.6	9.7	18.1	9.7	10.1
Madmoiselle	21.7	12.3	9.4	20.8	10.1	21.4	8.3	17.0	10.1	6.8
McCall's	28.1	21.4	18.1	26.8	19.5	27.0	17.0	22.8	18.4	17.4
National Enquirer	28.7	20.8	17.3	27.5	19.1	28.2	16.7	24.2	18.1	16.9
National Geographic	26.8	20.1	16.8	26.4	18.3	27.1	15.2	23.1	16.9	15.9
Newsweek	24.4	16.5	12.9	23.7	14.6	24.2	11.7	19.7	13.2	12.3
Parade	45.8	41.0	38.3	45.3	39.9	46.2	37.7	43.6	39.1	38.1
Parents	22.0	13.6	9.7	21.1	11.5	21.8	8.7	17.3	10.5	9.1
People	32.1	24.4	22.2	31.1	22.8	31.5	21.0	27.8	21.9	21.1
Prevention	21.8	13.7	9.8	20.8	11.8	21.9	8.7	17.3	10.7	9.2
Reader's Digest	35.6	30.7	27.6	35.1	29.1	35.2	26.1	31.9	27.6	27.0
Redbook	24.8	17.2	14.2	23.8	15.4	24.1	13.0	19.8	14.8	13.2
Soap Opera Digest	21.6	12.9	8.8	20.6	10.9	21.5	8.1	16.9	10.0	8.4
Southern Living	21.6	14.1	9.9	21.2	11.9	22.0	8.7	17.3	10.8	9.4
Sports Illustrated	21.3	13.0	9.1	20.6	11.1	21.3	8.1	16.9	9.8	8.5
Star	25.1	16.4	12.8	23.8	14.7	24.9	12.2	20.5	13.7	12.3
Sunday Magazine Net.	36.7	30.0	27.4	35.9	28.6	36.4	26.5	33.0	27.9	26.7
TV Guide	38.9	31.6	29.5	37.5	30.4	38.3	29.0	35.0	29.9	28.8
Time	27.1	19.4	16.4	26.8	17.7	26.9	15.1	22.9	16.3	15.5
USA Weekend	30.0	23.0	19.4	29.2	21.1	30.0	18.4	25.8	20.1	18.9
Woman's Day	28.3	22.3	19.4	26.0	20.5	27.8	18.0	24.4	19.8	18.3
Woman's World	22.0	13.8	10.1	20.6	11.8	21.5	8.9	17.2	10.9	9.2

U.S. Total : 92,184,000 (Adult Females)	McCall's.	National Enquirer	National Geo-graphic	Newsweek	Parade	Parents	People	Pre-vention	Reader's Digest	Redbook
Single Issue Rating	13.8	13.2	12.0	8.3	35.3	4.9	18.2	4.9	23.4	9.6
Self-Pair Rating	19.7	18.5	16.6	12.3	43.9	7.3	26.4	6.9	31.3	14.1
Better Homes & Gardens	28.1	28.7	26.8	24.4	45.8	22.0	32.1	21.8	35.6	24.8
Cosmopolitan	21.4	20.8	20.1	16.5	41.0	13.6	24.4	13.7	30.7	17.2
Ebony	18.1	17.3	16.8	12.9	38.3	9.7	22.2	9.8	27.6	14.2
Family Circle	26.8	27.5	26.4	23.7	45.3	21.1	31.1	20.8	35.1	23.8
Glamour	19.5	19.1	18.3	14.6	39.9	11.5	22.8	11.8	29.1	15.4
Good Housekeeping	27.0	28.2	27.1	24.2	46.2	21.8	31.5	21.9	35.2	24.1
House Garden	17.0	16.7	15.2	11.7	37.7	8.7	21.0	8.7	26.1	13.0
Ladies' Home Journal	22.8	24.2	23.1	19.7	43.6	17.3	27.8	17.3	31.9	19.8
Life	18.4	18.1	16.9	13.2	39.1	10.5	21.9	10.7	27.6	14.8
Madmoiselle	17.4	16.9	15.9	12.3	38.1	9.1	21.1	9.2	27.0	13.2
McCall's	19.7	24.2	23.6	20.2	43.6	17.7	28.4	17.7	32.2	20.2
National Enquirer	24.2	18.5	23.6	20.3	44.0	17.3	27.8	17.4	32.7	21.2
National Geographic	23.6	23.6	16.6	18.2	42.2	16.1	27.1	15.8	30.8	20.0
Newsweek	20.2	20.3	18.2	12.3	39.9	12.7	23.7	12.5	28.8	16.7
Parade	43.6	44.0	42.2	39.9	43.9	38.5	46.0	38.3	49.5	41.0
Parents	17.7	17.3	16.1	12.7	38.5	7.3	21.7	9.5	27.0	13.5
People	28.4	27.8	27.1	23.7	46.0	21.7	26.4	22.0	36.5	25.1
Prevention	17.7	17.4	15.8	12.5	38.3	9.5	22.0	6.9	26.4	13.6
Reader's Digest	32.2	32.7	30.8	28.8	49.5	27.0	36.5	26.4	31.3	29.6
Redbook	20.2	21.2	20.0	16.7	41.0	13.5	25.1	13.6	29.6	14.1
Soap Opera Digest	17.3	16.2	15.7	12.1	38.1	8.8	21.0	9.0	26.5	13.1
Southern Living	17.7	17.6	16.0	12.7	38.1	9.7	22.2	9.6	26.7	13.8
Sports Illustrated	17.3	16.8	15.3	11.7	37.6	8.8	21.0	9.0	26.3	13.2
Star	20.7	18.0	19.7	16.1	40.8	12.7	24.1	13.0	29.7	17.0
Sunday Magazine Net.	33.4	34.0	32.1	29.5	47.5	27.2	36.3	27.2	41.4	30.2
TV Guide	35.4	33.7	34.5	32.0	51.9	29.4	37.8	29.5	42.0	32.4
Time	23.5	23.4	21.0	17.4	42.1	16.0	26.0	16.0	31.4	19.8
USA Weekend	26.3	26.3	25.0	21.8	47.9	19.1	30.2	19.0	34.1	22.8
Woman's Day	24.8	25.6	24.4	21.4	44.2	18.8	29.1	18.4	33.1	21.4
Woman's World	17.7	17.2	16.2	12.9	38.5	9.7	21.8	9.6	26.6	13.6

U.S. Total : 92,184,000 (Adult Females)	Soap Opera Digest	Southern Living	Sports Illustrated	Star	Sunday Magazine Network	TV Guide	Time	USA Weekend	Woman's Day	Woman's World
Single Issue Rating	4.2	5.1	4.3	8.5	23.6	26.1	11.9	14.8	14.9	5.2
Self-Pair Rating	5.9	7.3	6.2	11.8	29.4	33.1	17.2	19.2	22.0	7.9
Better Homes & Gardens	21.6	21.6	21.3	25.1	36.7	38.9	27.1	30.0	28.3	22.0
Cosmopolitan	12.9	14.1	13.0	16.4	30.0	31.6	19.4	23.0	22.3	13.8
Ebony	8.8	9.9	9.1	12.8	27.4	29.5	16.4	19.4	19.4	10.1
Family Circle	20.6	21.2	20.6	23.8	35.9	37.5	26.8	29.2	26.0	20.6
Glamour	10.9	11.9	11.1	14.7	28.6	30.4	17.7	21.1	20.5	11.8
Good Housekeeping	21.5	22.0	21.3	24.9	36.4	38.3	26.9	30.0	27.8	21.5
House Garden	8.1	8.7	8.1	12.2	26.5	29.0	15.1	18.4	18.0	8.9
Ladies' Home Journal	16.9	17.3	16.9	20.5	33.0	35.0	22.9	25.8	24.4	17.2
Life	10.0	10.8	9.8	13.7	27.9	29.9	16.3	20.1	19.8	10.9
Madmoiselle	8.4	9.4	8.5	12.3	26.7	28.8	15.5	18.9	18.3	9.2
McCall's	17.3	17.7	17.3	20.7	33.4	35.4	23.5	26.3	24.8	17.7
National Enquirer	16.2	17.6	16.8	18.0	34.0	33.7	23.4	26.3	25.6	17.2
National Geographic	15.7	16.0	15.3	19.7	32.1	34.5	21.0	25.0	24.4	16.2
Newsweek	12.1	12.7	11.7	16.1	29.5	32.0	17.4	21.8	21.4	12.9
Parade	38.1	38.1	37.6	40.8	47.5	51.9	42.1	47.9	44.2	38.5
Parents	8.8	9.7	8.8	12.7	27.2	29.4	16.0	19.1	18.8	9.7
People	21.0	22.2	21.0	24.1	36.3	37.8	26.0	30.2	29.1	21.8
Prevention	9.0	9.6	9.0	13.0	27.2	29.5	16.0	19.0	18.4	9.6
Reader's Digest	26.5	26.7	26.3	29.7	41.4	42.0	31.4	34.1	33.1	26.6
Redbook	13.1	13.8	13.2	17.0	30.2	32.4	19.8	22.8	21.4	13.6
Soap Opera Digest	5.9	9.1	8.1	11.7	26.8	28.3	15.5	18.4	18.3	9.1
Southern Living	9.1	7.3	9.1	13.3	27.7	29.7	16.4	19.2	18.6	9.9
Sports Illustrated	8.1	9.1	6.2	12.2	26.6	28.7	15.0	18.6	18.4	9.2
Star	11.7	13.3	12.2	11.8	30.1	30.9	19.3	22.0	21.6	12.7
Sunday Magazine Net.	26.8	27.7	26.6	30.1	29.4	43.6	31.6	34.9	34.3	27.5
TV Guide	28.3	29.7	28.7	30.9	43.6	33.1	34.1	37.1	35.9	29.3
Time	15.5	16.4	15.0	19.3	31.6	34.1	17.2	24.9	24.4	16.3
USA Weekend	18.4	19.2	18.6	22.0	34.9	37.1	24.9	19.2	26.8	19.2
Woman's Day	18.3	18.6	18.4	21.6	34.3	35.9	24.4	26.8	22.0	17.9
Woman's World	9.1	9.9	9.2	12.7	27.5	29.3	16.3	19.2	17.9	7.9

Source: Simmons Market Research Bureau, Inc. (1988). Simmons Study of Media Markets (M-4).

C.2. ADULT MALES MARKET

U.S. Total : 84,066,000	Better Homes & Gardens	Business Week	Car and Driver	Ebony	Field & Stream	GQ	Good House-keeping	Jet	Life	Money
Single Issue Rating	5.6	5.0	4.3	4.3	9.4	3.7	3.4	3.9	6.3	4.2
Self-Pair Rating	8.4	7.2	6.3	5.7	13.7	5.8	5.5	5.3	10.1	6.2
Better Homes & Gardens	8.4	10.2	9.6	9.7	14.2	9.1	8.3	9.5	11.4	9.5
Business Week	10.2	7.2	9.0	9.1	13.9	8.3	8.1	8.9	10.7	8.4
Car and Driver	9.6	9.0	6.3	8.4	13.3	7.6	7.6	8.1	10.1	8.2
Ebony	9.7	9.1	8.4	5.7	13.4	7.5	7.6	6.2	10.1	8.2
Field & Stream	14.2	13.9	13.3	13.4	13.7	12.8	12.5	13.2	14.7	13.2
Gentlemen's Quarterly	9.1	8.3	7.6	7.5	12.8	5.8	7.0	7.1	9.5	7.6
Good Housekeeping	8.3	8.1	7.6	7.6	12.5	7.0	5.5	7.3	9.4	7.4
Jet	9.5	8.9	8.1	6.2	13.2	7.1	7.3	5.3	9.5	8.0
Life	11.4	10.7	10.1	10.1	14.7	9.5	9.4	9.5	10.1	10.0
Money	9.5	8.4	8.2	8.2	13.2	7.6	7.4	8.0	10.0	6.2
National Enquirer	13.3	12.8	12.0	11.7	16.5	11.4	11.2	11.4	13.6	12.1
National Geographic	18.8	18.2	18.0	18.5	22.2	17.7	17.1	18.3	19.3	17.8
Newsweek	16.0	14.8	14.9	15.0	19.4	14.3	14.1	15.0	16.0	14.5
Outdoor Life	12.4	12.0	11.1	11.4	13.9	10.7	10.3	11.0	12.9	11.2
Parade	38.5	38.4	37.8	37.8	41.7	37.5	37.3	37.7	39.2	37.5
People	15.6	15.1	14.5	14.6	19.5	13.9	13.8	14.5	15.8	14.3
Playboy	14.0	13.2	12.4	12.5	17.1	12.0	12.1	12.2	14.1	12.6
Popular Mechanics	10.7	10.2	9.2	9.7	13.8	9.0	8.8	9.4	11.4	9.4
Popular Science	9.5	9.0	8.1	8.5	13.0	7.8	7.5	8.2	10.1	8.2
Reader's Digest	22.8	23.0	22.7	22.8	26.4	22.4	21.4	22.6	23.9	22.2
Road & Track	9.0	8.5	6.9	7.9	12.5	7.1	7.0	7.6	9.4	7.6
Rolling Stone	9.2	8.5	7.7	7.9	12.7	7.0	7.2	7.6	9.5	7.9
Sports Afield	9.4	8.7	8.1	8.2	11.7	7.5	7.3	7.9	9.8	8.0
Sports Illustrated	22.2	21.5	20.9	21.1	24.8	20.3	20.6	20.8	22.2	20.8
Star	9.2	8.7	7.8	7.7	12.8	7.3	7.1	7.5	9.7	7.9
Sunday Magaznie Net.	28.9	28.2	27.8	27.9	32.4	27.6	27.5	27.8	29.3	27.7
TV Guide	25.4	25.1	24.2	24.1	28.3	24.0	23.8	23.9	25.6	24.5
Time	19.2	18.2	18.0	18.2	22.5	17.4	17.4	18.1	18.9	17.6
USA Weekend	19.6	19.2	18.7	18.8	22.6	18.2	17.9	18.5	20.3	18.4
U.S. News & World	12.7	11.8	11.7	12.0	16.2	11.2	11.0	11.8	13.4	11.3

U.S. Total : 84,066,000 (Adult Males)	National Enquirer	National Geo-graphic	Newsweek	Outdoor Life	Parade	People	Playboy	Popular Mechanics	Popular Science	Reader's Digest
Single Issue Rating	8.2	14.6	11.3	7.2	35.3	11.1	8.9	5.5	4.3	19.2
Self-Pair Rating	11.7	19.8	16.2	10.9	43.9	16.4	12.8	7.9	6.7	24.8
Better Homes & Gardens	13.3	18.8	16.0	12.4	38.5	15.6	14.0	10.7	9.5	22.8
Business Week	12.8	18.2	14.8	12.0	38.4	15.1	13.2	10.2	9.0	23.0
Car and Driver	12.0	18.0	14.9	11.1	37.8	14.5	12.4	9.2	8.1	22.7
Ebony	11.7	18.5	15.0	11.4	37.8	14.6	12.5	9.7	8.5	22.8
Field & Stream	16.5	22.2	19.4	13.9	41.7	19.5	17.1	13.8	13.0	26.4
Gentlemen's Quarterly	11.4	17.7	14.3	10.7	37.5	13.9	12.0	9.0	7.8	22.4
Good Housekeeping	11.2	17.1	14.1	10.3	37.3	13.8	12.1	8.8	7.5	21.4
Jet	11.4	18.3	15.0	11.0	37.7	14.5	12.2	9.4	8.2	22.6
Life	13.6	19.3	16.0	12.9	39.2	15.8	14.1	11.4	10.1	23.9
Money	12.1	17.8	14.5	11.2	37.5	14.3	12.6	9.4	8.2	22.2
National Enquirer	11.7	21.5	18.4	14.4	40.5	17.5	15.9	13.1	12.0	25.3
National Geographic	21.5	19.8	22.9	20.5	43.7	23.3	21.9	18.9	17.7	28.9
Newsweek	18.4	22.9	16.2	17.6	41.8	19.8	18.7	16.1	14.7	27.3
Outdoor Life	14.4	20.5	17.6	10.9	40.3	17.3	15.2	11.9	10.9	24.7
Parade	40.5	43.7	41.8	40.3	43.9	41.3	40.9	39.1	37.7	46.7
People	17.5	23.3	19.8	17.3	41.3	16.4	18.1	15.8	14.7	27.4
Playboy	15.9	21.9	18.7	15.2	40.9	18.1	12.8	13.8	12.7	26.2
Popular Mechanics	13.1	18.9	16.1	11.9	39.1	15.8	13.8	7.9	8.4	23.3
Popular Science	12.0	17.7	14.7	10.9	37.7	14.7	12.7	8.4	6.7	22.2
Reader's Digest	25.3	28.9	27.3	24.7	46.7	27.4	26.2	23.3	22.2	24.8
Road & Track	11.4	17.5	14.4	10.5	37.7	14.0	11.9	8.6	7.6	22.3
Rolling Stone	11.5	17.6	14.3	10.7	37.6	13.9	11.9	9.0	7.8	22.4
Sports Afield	11.7	17.9	14.7	9.8	38.0	14.6	12.3	9.1	8.0	22.2
Sports Illustrated	24.1	29.0	26.0	23.3	45.9	25.6	23.9	22.1	21.3	33.1
Star	10.5	17.8	14.7	10.5	37.8	14.0	12.2	9.1	7.9	22.2
Sunday Magaznie Net.	31.2	35.2	32.6	30.7	48.4	32.6	31.5	28.9	27.9	38.9
TV Guide	26.4	32.4	29.7	26.6	49.1	28.5	27.6	25.4	24.5	35.5
Time	21.5	25.5	22.3	20.9	43.8	22.8	21.8	19.1	17.9	29.9
USA Weekend	21.9	27.0	24.3	21.0	47.7	24.4	22.3	19.5	18.4	31.0
U.S. News & World	15.5	20.1	17.0	14.5	39.8	17.6	15.9	12.8	11.6	24.7

U.S. Total : 84,066,000 (Adult Males)	Road & Track	Rolling Stone	Sports Afield	Sports Illustrated	Star	Sunday Magazine Network	TV Guide	Time	USA Weekend	U.S. News & World
Single Issue Rating	3.7	3.8	4.0	17.9	3.8	25.0	21.3	14.8	14.9	8.0
Self-Pair Rating	5.5	5.6	6.1	24.5	5.8	31.0	27.5	21.1	19.1	11.7
Better Homes & Gardens	9.0	9.2	9.4	22.2	9.2	28.9	25.4	19.2	19.6	12.7
Business Week	8.5	8.5	8.7	21.5	8.7	28.2	25.1	18.2	19.2	11.8
Car and Driver	6.9	7.7	8.1	20.9	7.8	27.8	24.2	18.0	18.7	11.7
Ebony	7.9	7.9	8.2	21.1	7.7	27.9	24.1	18.2	18.8	12.0
Field & Stream	12.5	12.7	11.7	24.8	12.8	32.4	28.3	22.5	22.6	16.2
Gentlemen's Quarterly	7.1	7.0	7.5	20.3	7.3	27.6	24.0	17.4	18.2	11.2
Good Housekeeping	7.0	7.2	7.3	20.6	7.1	27.5	23.8	17.4	17.9	11.0
Jet	7.6	7.6	7.9	20.8	7.5	27.8	23.9	18.1	18.5	11.8
Life	9.4	9.5	9.8	22.2	9.7	29.3	25.6	18.9	20.3	13.4
Money	7.6	7.9	8.0	20.8	7.9	27.7	24.5	17.6	18.4	11.3
National Enquirer	11.4	11.5	11.7	24.1	10.5	31.2	26.4	21.5	21.9	15.5
National Geographic	17.5	17.6	17.9	29.0	17.8	35.2	32.4	25.5	27.0	20.1
Newsweek	14.4	14.3	14.7	26.0	14.7	32.6	29.7	22.3	24.3	17.0
Outdoor Life	10.5	10.7	9.8	23.3	10.5	30.7	26.6	20.9	21.0	14.5
Parade	37.7	37.6	38.0	45.9	37.8	48.4	49.1	43.8	47.7	39.8
People	14.0	13.9	14.6	25.6	14.0	32.6	28.5	22.8	24.4	17.6
Playboy	11.9	11.9	12.3	23.9	12.2	31.5	27.6	21.8	22.3	15.9
Popular Mechanics	8.6	9.0	9.1	22.1	9.1	28.9	25.4	19.1	19.5	12.8
Popular Science	7.6	7.8	8.0	21.3	7.9	27.9	24.5	17.9	18.4	11.6
Reader's Digest	22.3	22.4	22.2	33.1	22.2	38.9	35.5	29.9	31.0	24.7
Road & Track	5.5	7.1	7.4	20.3	7.2	27.5	23.8	17.5	18.1	11.3
Rolling Stone	7.1	5.6	7.6	20.5	7.4	27.6	23.8	17.4	18.1	11.2
Sports Afield	7.4	7.6	6.1	20.7	7.6	28.0	24.4	18.0	18.1	11.5
Sports Illustrated	20.3	20.5	20.7	24.5	20.6	37.2	34.0	28.3	29.8	23.6
Star	7.2	7.4	7.6	20.6	5.8	27.7	23.6	17.8	18.2	11.5
Sunday Magaznie Net.	27.5	27.6	28.0	37.2	27.7	31.0	41.5	34.5	35.9	30.4
TV Guide	23.8	23.8	24.4	34.0	23.6	41.5	27.5	32.3	32.9	27.5
Time	17.5	17.4	18.0	28.3	17.8	34.5	32.3	21.1	27.3	20.1
USA Weekend	18.1	18.1	18.1	29.8	18.2	35.9	32.9	27.3	19.1	21.6
U.S. News & World	11.3	11.2	11.5	23.6	11.5	30.4	27.5	20.1	21.6	11.7

Source: Simmons Market Research Bureau, Inc. (1988). Simmons Study of Media Markets (M-4).

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BIOGRAPHICAL SKETCH

Jungsik Cho is a doctoral candidate in the College of Journalism and Communications at the University of Florida. He received a Bachelor of Arts degree in mass communication at Yonsei University in Seoul, Korea. In 1985, he came to the United States and started his graduate studies at the University of Texas at Austin where he earned a Master of Arts degree in advertising. His current research focuses on advertising media and on copy research in advertising. Some of this research has been published in the Journalism Educator, Journal of Media Planning, and in the proceedings of the American Academy of Advertising and of the International Communications Association.

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Kent M. Lancaster
Kent M. Lancaster, Chairman
Professor of Journalism and Communications

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Joseph R. Pisani
Joseph R. Pisani
Professor of Journalism and Communications

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Frank N. Pierce
Frank N. Pierce
Professor of Journalism and Communications

I certify that I have read this study and that in my opinion it conforms to acceptable standards of scholarly presentation and is fully adequate, in scope and quality, as a dissertation for the degree of Doctor of Philosophy.

Robert D. Emerson
Robert D. Emerson
Professor of Food and Resource Economics

This dissertation was submitted to the Graduate Faculty of the College of Journalism and Communications and to the Graduate School and was accepted as partial fulfillment of the requirements for the degree of Doctor of Philosophy.

December 1992

Ralph L. Lowenstein

Dean, College of Journalism and Communications

Dean, Graduate School